

Exploration of Shared Mental Models among 3x3 Basketball Players: Cognitive Mapping of Social Media Data

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Abstract Shared mental models are a compelling concept that highlights the importance of shared understanding among team members to achieve improved team performance. This study aimed to extract individual mental models from social media posts and explore differences in the shared mental models of successful and unsuccessful teams on example of the FIBA 3x3 Basketball World Cup 2023. Mental models were derived through semantic network analysis employing the textual analytical software Automap. The sample consisted of 368 posts from 39 team members, collected from platforms such as Facebook, X and Instagram. Significant disparities between successful and unsuccessful teams were uncovered, with the former displaying a greater number of concepts and statements, having larger shared cognitive maps. Additionally, the analysis offered insights into gender specific team sharedness, revealing that even though male team members were less verbal, they exhibited a higher degree of sharedness compared to their female counterparts. This study demonstrates the potential of social media data for constructing shared mental models and offers two key contributions: 1) It provides empirical evidence to the literature, and 2) it highlights the viability of social media as a tool for evaluating shared mental models, opening new avenues for research in the field.

Keywords shared mental models; cognitive map; social media data; textual analysis

1 Introduction

The shared mental model (SMM) concept delves into specifics of how a group of people develops collective representations. Widely employed in organizational studies, it involves formation by team members ‘accurate explanations and expectations for the task’. Consequently, they ‘coordinate their actions and adapt their behavior to demands of the task and other team members’^[1]. Proven to be a crucial factor, this concept significantly contributes to enhancing team efficiency and overall team performance.

The concept of team mental model closely tied with SMM, although there are nuanced differences in the literature. In this study, both terms denote a shared understanding among

team members, represented by shared cognitive structures, and are used interchangeably.

There is an abundance of research evidence in the literature showcasing the positive impacts of SMM development on team outputs. The concept of SMM has continuously evolved within the field of business economics^[2], offering a dynamic foundation for fostering effective collaboration and cohesive team performance. For instance, the mediating role of SMM development between team learning behavior and team performance has been evident in various contexts, such as teacher teams^[3], service management teams^[4], student teams during business simulation^[5] among others. The application of SMM in action team learning enables members of the team to enhance their collective problem-solving skills^[6].

SMMs refer to the shared understanding and knowledge structures that team members collectively develop over time, influencing the success of a team. It formed through interaction processes, such as coordination, communication, and collaboration^[7]. Critical impact of SMMs on team performance becomes evident through improved communication and coordination^[8]. Successful teams tend to exhibit a higher degree of sharedness among teammates with more verbal expressions^[9]. Moreover, both explicit and implicit coordination exists within a team and facilitates its effectiveness alongside each other^[10].

The cultivation of SMMs necessitates quality communication within a team, fostering idea sharing and convergence through a favorable working climate^[11]. The convergence of individual mental models, leading to the adaptation of information communication technologies, allows teams to maintain effectiveness^[8,12]. When teammates share a common understanding of the team's goals and each member's role, the chances of misunderstandings are reduced. This shared understanding enhances the coordination of responsibilities and knowledge, improves interaction patterns, and promotes processing strategies, enabling team members to work more efficiently towards common goals^[13].

Moreover, shared understanding facilitates the effectiveness of decision making processes and the timeliness of working plans, further improving team outcomes^[14]. When team members collectively share mental representation of task processes and goals, decision-making becomes faster and more cohesive, reducing the time required to reach a consensus and enabling rapid strategy adaptation^[15].

Furthermore, the development of SMMs through team orientation directly contributes to team effectiveness and adaptability, with the mediating role of mutual performance monitoring and back up behavior^[16]. These findings emphasize the importance of developing SMMs in teamwork.

The development of SMM is particularly crucial among agile teams operating in fast-changing, sometimes unpredictable or uncontrollable working environments, such as military settings, medical teams or sports teams. Efficient and cohesive teamwork is vital for both military and medical teams, requiring not only technical skills but also high-quality teamwork^[17]. The level of sharedness among team members significantly impacts a team's capacity to engage in purposeful and coordinated actions, ultimately contributing to enhanced team performance^[18].

Sport teams are often chosen by researchers for study due to the transparent process of team interactions, observed either on-site or through media translation, team cooperation, exhibited with a diverse range of roles, immediate feedback, clear objectives and measurable results. Shared understanding evolves through the foundation of an effective SMMs, requiring a synthesis of factors like collective experience, cohesive team dynamics, and efficient communication approaches. A shared understanding among sportsmen, developed through shared experiences, promotes coordination based upon prediction, ultimately enabling effective performance^[19]. Team training serves as one of the main contributors to shared experiences among sports team members, leading to the evolution of the level of a shared content^[20].

The development of SMMs further improves team performance by fostering nonverbal interactions and implicit coordination^[21]. SMMs developed through collective training diminish the necessity of verbal communication among players^[22]. It facilitates interpersonal coordination — a crucial factor in interactive sports settings with constantly changing contexts and achievable through group actions^[23]. Group actions grounded in shared affordances (perception of what a team member can do in a particular situation, identifying opportunities for action), lead to the creation of interpersonal synergies between players and the emergence of coordinated behaviors in sports teams^[24].

The development of SMMs emerges as a key driver of team success across varied settings. The current study investigates such a relationship on an illustrative example of sports teams, where the need for rapid adaptation and implicit coordination in an agile environment significantly influences the results of team cooperation. The shared understanding among team members, developed through collective experiences, results in enhanced team performance. The literature reviewed emphasizes the pivotal role of SMMs in promoting cohesion, creating interpersonal synergies and fostering coordinated behaviors. This, in turn, promotes overall team effectiveness, ultimately contributing to successful team outputs.

To sum up, the study of shared mental models addresses a crucial managerial goal — improving team performance. Evidence from the literature demonstrates that a higher level of sharedness among team members enhances coordination, communication, and overall efficiency. By fostering shared mental models, managers can strengthen collaboration, streamline team processes, reduce misunderstandings, and achieve superior outcomes. Therefore, this area of study is instrumental in optimizing team dynamics and efficiency.

This research aims to contribute to existing knowledge by providing practical evidence regarding distinctions in shared cognition between successful and unsuccessful teams. A novel approach is employed by leveraging social media data to construct and analyze individuals' mental models. To the best of the author's knowledge, this study is pioneering in drawing team cognitive maps through the analysis of social media posts. This method offers new possibilities for researchers in the sphere, eliminating response bias inherent in interviews or surveys. While it poses challenges such as dealing with a large volume of unnecessary data and time-consuming cleaning processes, it serves as a valuable source for constructing mental representations of

platform users.

The present study is structured as follows: The ‘Introduction’ section outlines the main research objective and incorporates a brief review of the literature. The ‘Methodology’ section provides a detailed account of the research methods employed. In the ‘Data’ section, both the data sources and the participant selection process are elucidated. The ‘Empirical analysis and discussion’ section presents the empirical evidence obtained in this study, accompanied by discussions of possible reasons and explanations for the observed results. Lastly, the section ‘Conclusions and implications’ summarizes the obtained results, emphasizes the contributions made, acknowledges the limitations encountered, and suggests potential avenues for further research.

2 Methodology

To construct individual mental models, semantic network analysis was performed. Semantic network analysis is a widely used method for analyzing textual data and constructing individual mental models, which serve as the foundation for developing shared mental models. Semantic network analysis involves the creation of a semantic map that consists of concepts — single or multiple interrelated words with a unified semantic meaning — and statements, which are links connecting two concepts^[25].

Semantic network analysis in this study aimed to reveal the shared understanding of team members towards the event and their shared values by identifying recurring patterns and themes in their social media posts. The analysis was conducted using the textual mining software Automap, version 3.0.10.42.

Data preprocessing involved two steps: Manual preprocessing and automated preprocessing through text refinement, preparation, and cleaning in Automap software. Manual preprocessing aimed to reduce errors during automated preprocessing and included conversion of particular words to add more clarity for further automated preprocessing. Automated preprocessing included removal of words or symbols that didn’t contribute to the understanding of semantic networks, such as punctuation, single letters, prepositions, etc. The main goal of preprocessing was to retain only meaningful concepts (key concepts) from the text for further analysis.

Coding procedures included data filtering and windowing. Filtering involved concept generalization and deletion, with the application of thesaurus (list of associations) and a delete list, containing noise words. Thesaurus included: (a) concepts with similar or identical meanings were coded as same concept (for example, ‘mom’ was coded as ‘mother’); (b) concepts with the same base were recorded into the same concept (for example, ‘won’ was coded as ‘win’, ‘team-mates’ – ‘teammate’); (c) applying bigrams or Ngrams – consolidation of two or more concepts into one, such as ‘United States of America’. The delete list contained noise words and irrelevant parts of the text, such as links.

Windowing, a method of coding the text as a map, involved placing relationships between pairs of concepts within a certain user-predefined window. Semantic networks of individual

cognitive maps were generated from filtered texts using window sizes of 2, 6, 10, and 100, incorporating bidirectional windowing settings and a paragraph as a stop unit.

The analysis of team cognitive maps revealed both a lossy intersection at 50%, indicating the presence of statements shared by at least two team members, and a true intersection, indicating statements shared by all members of a team.

Finally, semantic networks were visualized using ORA-LITE software (version ORA 3.0.9.142) to illustrate the connections and relationships between concepts, providing a graphical representation of how information is expressed by the players.

The research methodology is presented as a roadmap, illustrated in Figure 1.

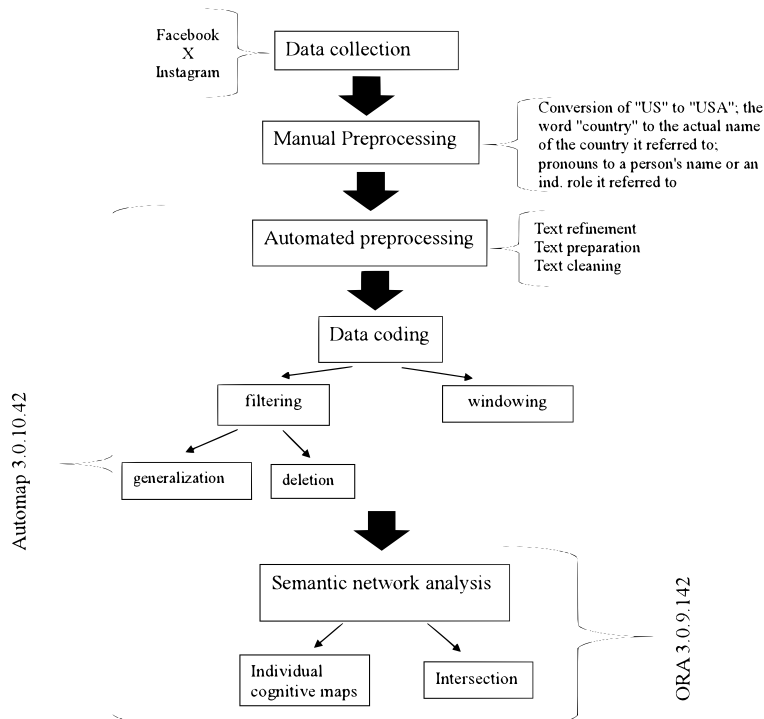


Figure 1 Roadmap of research methodology

3 Data

Individual mental models, defined as ‘a concentrated, personally constructed, internal conception of external phenomena or experience that affects how a person acts’^[26], can be assessed by studying the expressions individuals share through social media platforms. These platforms serve as invaluable sources of publicly available information and have become widely used in various research projects. Through social media accounts, people express their thoughts, opinions, and preferences, making it possible to collect and analyze data for different research purposes. Examining the linguistic and stylistic features of users’ posts on these platforms provides researchers with valuable insights into social media users’ intentions, views, and mental states,

among other aspects. The independence of participants in expressing themselves on these platforms reduces social desirability bias, eliminates acquiescence bias during surveys, and mitigates the possibility of interviewer bias.

The current study utilizes social media platforms such as Facebook, X (formerly Twitter) and Instagram as sources for textual analysis. These platforms, being widely used across many countries, ensure the presence of data from most team members, considering diverse social media preferences in different countries. Data represented from different social media platforms allows for data comparison and ensures different user behavior was captured.

Basketball teams were selected as the focal point for constructing and evaluating SMMs, using the FIBA (International Basketball Federation) 3x3 Basketball World Cup 2023 as an illustrative example. Unlike, traditional 5-on-5 basketball game, 3x3 basketball is played by two teams of three players each on a half-court with one basket^[27]. The rapid pace and dynamic nature of 3x3 games made this variation of basketball globally popular, offering a rich environment for exploration of team dynamics and SMMs.

The FIBA 3x3 World Cup 2023 took place in Vienna, Austria from May 30 to June 4. The competition comprised both men's and women's 3x3 tournaments, each with 20 participating teams. Each team consisted of four members — three players and one substitute. Players were selected by their national federations to represent their respective countries. As players do not form their teams, it allows to measure the team's mental model constructed during training within a limited timeframe. Therefore, individual mental models were extracted from social media posts during the period from May 1 to June 4 — one month before the event until the last day of the event. This provides sufficient time period coverage for data representativeness.

Teams were selected based on their standings' statistics (refer to Appendix A), with the top 6 and bottom 6 teams for both men and women considered. Three teams from the top 6 and three teams from the bottom 6 in both the men's and women's tournaments were chosen based on data availability to represent the successful and unsuccessful teams, respectively. In this context, successful teams ranked in the top 6 according to the national teams' standings, while unsuccessful teams ranked in the bottom 6.

Information about team members and their social media accounts was obtained through the official FIBA website. The author established acceptability criteria for social media accounts found on different platforms, but unverified on FIBA website: (1) The account holder follows or is followed by any other team member, verified by FIBA. (2) The social media account is followed by an official basketball community account — either the FIBA account or the account of the national basketball organization. (3) The account is tagged in discussions related to the event. Accounts meeting any of these criteria were verified as belonging to one of the players.

A total of 96 team members' social media accounts were searched and checked, and 39 were ultimately selected for further analysis. Missing data was deemed acceptable if at least 3 out of 4 team members were included in the analysis (representing 75% of the team). The final dataset comprises 368 manually collected original posts, including 56 posts on Facebook, 181

posts on X and 146 posts on Instagram. Fifteen duplicate posts, such as identical content shared by the same team member across different platforms, were excluded from the final dataset for semantic network analysis of successful and unsuccessful teams (refer to section 4.1). However, these duplicate posts were preserved for the purpose of comparing the application of different platforms (refer to section 4.2).

The posts encompassed various types, such as original posts, reposts, replies, quotes, and more. Reposts, replies, and quotes were treated the same as original posts in the dataset because when a user reposts information, it also reflects their cognitive map, expressing co-feelings and shared ideas.

The composition of the data revealed significant disparities between the cognitive maps of successful and unsuccessful teams, a finding that aligns with previous research in this area. This consistency supports the generalizability of these trends across various contexts and populations. Consequently, the data presented is not only informative but also demonstrates its representativeness.

4 Empirical Analysis and Discussion

Throughout the process of semantic network analysis, two primary questions were addressed. Firstly, whether there exists a systematic difference in the team mental models between successful and unsuccessful teams, as evidenced in the evaluation of their respective cognitive maps. Secondly, whether social media posts can effectively convey individual mental models and contribute to the assessment of SMMs. Therefore, the findings of this research not only add empirical evidence to the literature on shared mental models but also introduce a novel, tested method for constructing shared cognitive maps, offering practical tools for managers and teams to assess and enhance collaboration and performance.

Individuals' cognitive maps, built using both unfiltered and filtered data, were compared to assess the sensitivity of the data to the filtering process. The results were then used to compare data from different social media platforms.

In the unfiltered dataset, a total of 2801 unique concepts were identified. Following the application of filtering, this number decreased to 981, with the range of concepts per map spanning from 1 to 225. Each text was analyzed both before and after filtering, resulting in a notable reduction in the count of concepts and statements per map (refer to Table 1). Without filtering, the number of statements varies from 7 to 14421 per map; after filtering, this range decreases to 0 to 6820 statements per map.

Table 1 demonstrates that filtering leads to a statistically significant reduction in both the number of concepts and statements per map. This reduction underscores the impact of filtering in refining the cognitive maps, providing a clearer and more focused representation of the underlying mental models.

4.1 Semantic Network Analysis of Successful and Unsuccessful Teams’ SMM

Semantic network analysis is a valuable tool for exploring potential variations in the number of concepts and statements between successful and unsuccessful teams. The individuals’ cognitive maps within both successful and unsuccessful teams were analyzed before and after applying text filtering. After filtering applied to texts, a significant reduction in the count of concepts and statements per map was observed for both successful and unsuccessful team members (refer to Table 2).

Statistically significant differences surfaced between successful and unsuccessful teams across all unfiltered and filtered concepts and statements. Successful teams demonstrated a more extensive utilization of concepts, expressing them in more diverse ways compared to unsuccessful teams. The application of filtering resulted in an equal reduction in both concepts and statements.

Table 2 underscores the findings, indicating that, on average, members of successful teams employ approximately twice as many concepts, constructing larger cognitive maps featuring nearly four times as many statements per map compared to members of unsuccessful teams.

In the context of constructing SMM, the emphasis should be on the extent of shared understanding among teammates, rather than solely focusing on a high volume of concepts and statements. Therefore, the extent of sharedness is presented in Table 3, revealing results for window sizes of 2, 6, 10, and 100. Successful teams demonstrated greater sharing, with larger maps and higher degrees of sharedness. The number of statements shared by 2 or more team members is larger for successful groups, trend is apparent even on the level of true intersection, where statements are shared by all team members. The average number of statements per network was also higher for successful teammates, suggesting a wider range of ideas and more intense discussions. These differences in concept application and cognitive maps persisted across all window sizes, even at the smallest window size of 2. These results underline the significance of shared cognitive structures among team members, suggesting implications for team cohesion and performance.

Table 1 Characteristics of individuals’ cognitive maps

	Average number of concepts per map	Average number of statements per map
Unfiltered	141.10 (126.79)	2332.59 (3100.87)
Filtered	58.90 (53.36)	947.08 (1562.10)
Wilcoxon Signed-Rank test	$Z = -6.95$ $p < 0.001$	$Z = -5.44$ $p < 0.001$

Note: Standard deviations are in parentheses. $N = 39$. Window size = 100. The Wilcoxon Signed-Rank test was applied to analyze the dependent dataset (paired samples before and after filtering) because the data did not meet the assumption of normality.

Other noteworthy findings were revealed for gender-specific semantic network analysis (refer to Table 3). Despite women's networks displaying a higher average number of links than men's networks, this gap reduced in the lossy intersection of 50%. On the level of true intersection, results were reversed, with more statements shared by all team members in men's teams.

In the case of a window size of 100, the average number of statements in women's teams is 3.27 times higher than the average number of statements in men's teams. The number of statements shared by two or more female team members is 2.44 times higher than statements shared by two or more male team members. Nevertheless, the number of statements shared by all team members for women's teams is 3.76 times less than those of men's teams (refer to Table 3). Using fewer statements in their posts (posts of men's team members) doesn't have a negative impact on the degree of sharedness. Men in our example are more straightforward and showcase greater sharedness at the level of the true intersection than women.

This trend continued when comparing successful men's teams and successful women's teams. While unsuccessful male teams demonstrated greater numbers in all statements (union), statements shared by two or more teammates, and statements shared by all teammates compared to unsuccessful female teams.

Table 2 Characteristics of individuals' cognitive maps for successful and unsuccessful team members

	Average number of concepts per map	Average number of statements per map
Successful teams		
Unfiltered	189.20 (143.88)	3665.80 (3790.02)
Filtered	77.90 (59.88)	1470.65 (1972.28)
Unsuccessful teams		
Unfiltered	90.47 (78.79)	929.21 (881.01)
Filtered	38.90 (35.91)	395.95 (567.28)
Mann-Whitney U test		
	$U = 106.50$	$U = 96.50$
Unfiltered	$Z = 2.33$ $p < 0.05$	$Z = 2.61$ $p < 0.01$
	$U = 112.00$	$U = 112.50$
Filtered	$Z = 2.18$ $p < 0.05$	$Z = 2.16$ $p < 0.05$

Note: Standard deviations are in parentheses. $N = 20$ for successful teams and $N = 19$ for unsuccessful teams. Window size = 100. The Mann-Whitney U test was applied to independent datasets where one or both did not follow a normal distribution according to the Shapiro-Wilk test.

Table 3 Team cognitive maps

Window size	2	6	10	100
Successful teams				
Average number of links (union)	299.33	1399.67	2264.67	9006.00
Lossy intersection 50%	26.00	111.33	181.67	672.67
True intersection	1.50	5.67	8.33	17.33
Unsuccessful teams				
Average number of links (union)	135.33	601.00	918.67	2410.33
Lossy intersection 50%	2.33	14.33	24.33	92.00
True intersection	0.00	0.17	0.17	2.50
Men's teams				
Average number of links (union)	163.00	733.33	1125.67	2675.00
Lossy intersection 50%	12.67	50.67	79.67	222.33
True intersection	1.17	4.17	5.83	15.67
Women's teams				
Average number of links (union)	271.67	1267.33	2057.67	8741.33
Lossy intersection 50%	15.67	75.00	126.33	542.33
True intersection	0.33	1.67	2.67	4.17
Successful men's teams				
Average number of links (union)	194.67	868.67	1334.00	3011.33
Lossy intersection 50%	22.67	80.67	124.67	292.67
True intersection	2.33	8.00	11.33	26.33
Successful women's teams				
Average number of links (union)	404.00	1930.67	3195.33	15000.67
Lossy intersection 50%	29.33	142.00	238.67	1052.67
True intersection	0.67	3.33	5.33	8.33
Unsuccessful men's teams				
Average number of links (union)	131.33	598.00	917.33	2338.67
Lossy intersection 50%	2.67	20.67	34.67	152.00
True intersection	0	0.33	0.33	5.00
Unsuccessful women's teams				
Average number of links (union) n	139.33	604.00	920.00	2482.00
Lossy intersection 50%	2.00	8.00	14.00	32.00
True intersection	0	0	0	0

Note: Using filtered texts. $N = 6$ for successful teams, 6 for unsuccessful teams, 6 for men's teams, 6 for women's teams, 3 for successful men's teams, 3 for successful women's teams, 3 for unsuccessful men's teams, 3 for unsuccessful women's teams.

Gender differences in expressing individual mental models may be explained by women's tendency to use more words to convey feelings and opinions. Even though male users' behavior differs from female users in the number of textually expressed statements on platforms, their level of sharedness at the true intersection is higher than that of women.

The observed higher level of sharedness among successful teams in Table 3, along with the greater number of concepts and statements displayed in Table 2 for successful teams compared to unsuccessful ones, prompts the question of whether a direct relationship exists between the quantity of concepts and team outcomes. If the number of concepts and statements per map is presumed to influence the level of sharedness among teammates, a potential misconception could arise, suggesting that increased social media activity and heightened online engagement lead to team success. To challenge this notion, the author conducted a comparison of sharedness levels between two teams — one successful and one unsuccessful — with similar average numbers of concepts and statements per map (refer to Figure 2).

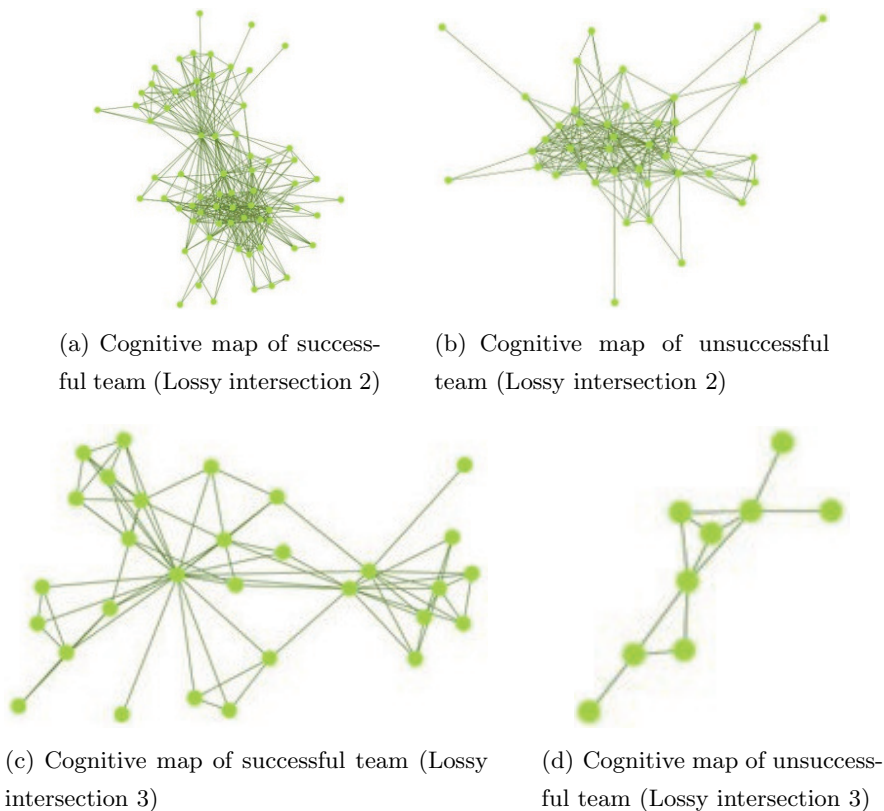


Figure 2 Differences in sharedness between a selected successful and an unsuccessful team

Note: The graphical representation was generated using ORA Software (version 3.0.9.142).

In Figure 2, a specific successful team and an unsuccessful team were carefully selected from the dataset, providing an in-depth exploration of sharedness dynamics. Each team was represented by 3 members. ‘Lossy intersection 2’ indicates sharedness among 2 team members, accounting for 66.67% of the team, while ‘Lossy intersection 3’ represents the true intersection where all team members share the statements.

Figure 2 brings to light distinct patterns within the SMMs of team members. Even with a similar average number of concepts and statements per map (87.67 concepts and 1026.67 links on average among members of the successful team, 90 concepts and 1132.67 links on average among members of the unsuccessful team), the successful team operates with a much larger team cognitive map, both at the level of lossy intersection 2 and at the true intersection with 100% of the team sharing the statements (refer to Appendix B). These findings suggest that semantic network analysis has proven to be efficient in detecting SMMs among basketball players. Members of successful teams not only employ more concepts and form more statements in their posts but also exhibit a higher level of sharedness among team members.

In conclusion, semantic network analysis revealed a statistically significant difference between successful and unsuccessful teams in how they express ideas through the number of statements and their level of sharedness. SMMs among team members proved to be an influential factor in team performance, and semantic network analysis effectively captured differences in cognitive maps among successful and unsuccessful teammates. Additional insights highlighted differences in cognitive structures between men and women, emphasizing more verbal expressions from female members and higher sharedness among male teammates.

4.2 Application of Different Social Media Platforms as Data Source for Individual Mental Models Construct

Interaction among social media users varies slightly from platform to platform. Facebook, X, and Instagram offer multiple services to their users, including posts, reposts, direct messages, photo and video sharing, among others. However, user preferences differ among platforms. For instance, Instagram users prefer posting photos with small textual captions, where textual analysis alone may not be sufficient, necessitating additional analytical methods, such as visual content analysis. In contrast, X and Facebook users tend to be more ‘talkative’ when sharing their posts. This diversity in user behavior implies that the application of data retrieved from different social media platforms may exhibit varying levels of efficiency for semantic network analysis purposes.

Moreover, individuals often use multiple platforms concurrently for various reasons, such as diversifying their online presence, engaging with different communities, and accessing various content and communication channels^[28].

To account for these platform-specific differences, individuals’ cognitive maps were constructed separately for three social media platforms: Facebook, X, and Instagram. These maps were analyzed both before and after applying text filtering. The results showed a statistically significant reduction in the count of concepts and statements per map for all three platforms after filtering (refer to Table 4).

The total number of platform users, as presented in Table 4, exceeds the total number of team members analyzed due to some individuals holding multiple social media accounts on different platforms. Instagram stands out with the highest number of users in the analysis, totaling 31 accounts from team members. However, despite this prevalence, Instagram accommodates the

Table 4 Characteristics of individuals' cognitive maps for different platforms' users

Platform	Average number of concepts per map			Average number of statements per map		
	Facebook	X	Instagram	Facebook	X	Instagram
Unfiltered	131.25	171.69	77.84	1365.00	3538.31	1084.55
	(76.38)	(146.95)	(77.79)	(786.65)	(3924.62)	(1548.07)
Filtered	56.75	71.23	32.10	650.67	1725.62	287.84
	(35.55)	(62.28)	(33.56)	(607.76)	(2205.57)	(571.89)
<i>t</i> -test	<i>t</i> = 5.74	-	-	-	-	-
	<i>p</i> < 0.001					
Wilcoxon	-	<i>Z</i> = -3.67	<i>Z</i> = -4.85	<i>Z</i> = -3.49	<i>Z</i> = -3.67	<i>Z</i> = -6.12
Signed-Rank test		<i>p</i> < 0.001	<i>p</i> < 0.001	<i>p</i> < 0.001	<i>p</i> < 0.001	<i>p</i> < 0.001

Note: Standard deviations are in parentheses. Window size equals to 100. $N = 12$ for Facebook, 31 for Instagram, and 13 for X. The paired *t*-test was applied to analyze the dependent datasets, while the Wilcoxon Signed-Rank test was used when the normality assumption was not met in one or both datasets.

fewest number of concepts and statements per map, averaging 77.84 unfiltered concepts and 1084.55 unfiltered statements.

The reduction in the number of concepts after applying filtering is consistent across Facebook, X, and Instagram, with reductions of 56.76%, 58.57%, and 58.78%, respectively, aligning with the overall dataset filtering process as displayed in Table 1. However, the impact of filtering on the number of statements is more pronounced in the Instagram data source, with a reduction of 73.46%, while Facebook and X data experienced reductions of 52.33% and 51.23%, respectively. Given these variations, it prompts the question of whether the reduction in Instagram data may influence results related to sharedness among team members, and furthermore, whether Instagram data is suitable for the current study, providing sufficient information to assess the degree of sharedness among team members. Hence, team cognitive maps were constructed specifically for Instagram platform users (refer to Table 5).

Table 5 Team cognitive maps constructed from Instagram data source

Teams	Average number of links that appear in any of the network (union)	Lossy intersection (50%)	True intersection
Successful	3487.00	242.00	18.50
Unsuccessful	380.00	4.50	0

Note: Using filtered data with a window size of 100; $N = 14$ members from 4 successful teams and 12 members from 4 unsuccessful teams.

Table 5 features Instagram users, with a minimum representation of at least 3 members per team. Although the dataset comprises a total of 31 Instagram users, only 26 of them are part

of teams that are included in Table 5.

To interpret sharedness grasped from Instagram data, the results in Table 5 were compared to the team cognitive mapping results for filtered text with a window size of 100 for successful and unsuccessful teams, as shown in Table 3. Sharedness among 50% of the team or higher for successful teams, displayed in Table 3 is 7.47% from number of links that appear in any of the network, and 0.19% of all links represent teams' true intersection. Results obtained from Instagram dataset differ slightly with 6.94% of the network being shared by 50% of the team and 0.53% of the network presenting true intersection. For unsuccessful teams, 3.82% of the network obtained from different social media platforms is shared by 50% of the team, whereas for the Instagram dataset, this number is 1.18% of the network. True intersection for unsuccessful teams among data retrieved from all three platforms is 0.1%, with no true intersection among unsuccessful players within Instagram platform.

In summary, these findings suggest that Instagram data requires more extensive filtering of the text. Additionally, relying solely on textual analysis of Instagram data may slightly affect results, as seen in the degree of sharedness of 50% among unsuccessful teammates, where Instagram data revealed only 1.18% of the network shared, compared to 3.82% when data obtained from different sources. Nevertheless, the comparison also demonstrated that even with a significant reduction in the number of statements after filtering, Instagram textual data can still be applied for individual mental model construction and teams' SMM evaluation, as it was able to capture significant differences between successful and unsuccessful teams.

5 Conclusions and Implication

This study explored the SMMs of 39 individuals across 12 basketball teams, employing semantic network analysis. The research revealed a substantial contrast between successful and unsuccessful teams in terms of expressing ideas, characterized by successful teams exhibiting a greater number of concepts and statements, along with larger cognitive maps shared among team members. These observations suggest explicitness, verbal richness, and enhanced communication within successful teams.

Investigating the level of sharedness among teams with similar averaged numbers of concepts and statements, the study confirmed the positive impact of sharedness on team outcomes. The findings imply that a positive relationship between the number of concepts and statements and team outcomes occurs only when there is an intermediate role of sharedness among team members. These findings are consistent with existing literature, underscoring the critical role of sharedness in fostering improved team performance.

Additionally, the analysis provided insights into team cognitive structural differences between men and women, showcasing more verbal expressions from female members and higher sharedness among male teammates. Notably, the study found that a higher level of sharedness in the lossy intersection at 50% does not guarantee greater sharedness on the true intersection, as revealed in gender-specific semantic network analysis (refer to Table 3).

Analyzing social media posts for constructing individual mental models proved effective across all three platforms. However, in the case of Instagram, while the extracted data was sufficient to understand team cognitive maps and differences in SMMs between successful and unsuccessful teams, additional visual data extraction and analysis could enhance the precision of the results. Despite this, the use of social media data for exploring SMMs among team members demonstrated efficiency and informativeness. Nevertheless, the process is time-consuming and requires extensive filtering before analysis.

The study, however, is not without its limitations. The dataset's small volume and variations in team members' attitudes toward social media platform usage may introduce bias. Some team members, exhibiting passive or no online presence, could impact the accuracy of social media posts in fully reflecting the mental representations of their authors. The factors related to team composition and training could influence both the level of sharedness among teammates and the behavior of users on social media accounts. For example, differences in shared training time and intensity among national teams could vary the level of shared experience. Additionally, the activities and promotional efforts of national basketball organizations, along with variations in team funding resources, may influence team members' interactions and the development of SMM within a team.

To the best of the author's knowledge, this paper presents a novel data source for the composition of SMM. Social media data have enriched many research areas by providing a vast corpus of data, and have also proven in this research to be applicable for the construction and evaluation of SMM. In addition to sports teams, which are considered as a case study in this paper, other team settings, such as business and public service teams, can benefit from the ability to timely evaluate team mental models and predict team outcomes based on current mental models.

Future research in the analysis of social media posts for individual mental model construction should concentrate on refining analytical techniques and exploring multimodal analysis by taking into consideration visual content. Moreover, interdisciplinary collaboration and integration of additional data sources can contribute to a more comprehensive understanding and exploration of the SMM concept.

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Appendix

A Teams’ standings on FIBA 3x3 World Cup 2023

Table A1 Teams’ standings			
Men’s standing		Women’s standing	
1	Serbia	1	The United States of America
2	The United States of America	2	France
3	Latvia	3	Australia
4	Brazil	4	China
5	Netherlands	5	Germany
6	Austria	6	Canada
7	Poland	7	Austria
8	France	8	Spain
9	Switzerland	9	Japan
10	Lithuania	10	Czech Republic
11	Belgium	11	Israel
12	Japan	12	Italy
13	Puerto Rico	13	Egypt
14	Israel	14	Brazil
15	Australia	15	Lithuania
16	Madagascar	16	Netherlands
17	Germany	17	Hungary
18	Mongolia	18	Mongolia
19	Hungary	19	Poland
20	Slovenia	20	Romania

Note: Information was retrieved from the official FIBA web resource:
<https://fiba3x3.com/2023/worldcup>.

B Statistics on Successful and Unsuccessful Teams with Similar Average Number of Concepts and Statements

Table B2 Statistics on selected successful and unsuccessful teams		
	Successful team	Unsuccessful team
Average number of concepts per map	87.67 (11.26)	90.00 (23.28)
Average number of statements per map	1026.67 (291.22)	1132.67 (515.68)
Number of concepts in the network	161.00	206.00
Number of statements in the network	5206.00	6322.00
Concepts' lossy intersection at 50%	68.00	42.00
Statements' lossy intersection at 50%	798.00	446.00
True intersection of concepts	30.00	12.00
True intersection of statements	78.00	14.00

Note: Standard deviations are in parentheses. $N = 1$ successful team and 1 unsuccessful team with three participants each. Semantic network analysis performed for filtered texts with window size equal to 100.