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Team Composition Revisited: A Team Member Attribute Alignment Approach

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Abstract
Research methods for studying team composition tend to employ either a variable-centered or person-centered approach. The variable-centered approach allows scholars to consider how patterns of attributes *between* team members influence teams, while the person-centered approach allows scholars to consider how variation in multiple attributes *within* team members influences subgroup formation and its effects. Team composition theory, however, is becoming increasingly sophisticated, assuming variation on multiple attributes both within and between team members—for example, in predicting how a team functions differently when its most assertive members are also optimistic rather than pessimistic. To support this new theory, we propose an *attribute alignment* approach, which complements the variable-centered and person-centered approaches by modeling teams as matrices of their members and their members' attributes. We first demonstrate how to calculate attribute alignment by determining the vector norm and vector angle between team members' attributes. Then, we demonstrate how the alignment of team member personality attributes (neuroticism and agreeableness) affects team relationship conflict. Finally, we discuss the potential of using the attribute alignment approach to enrich broader team research.

Keywords
team composition, attribute alignment, vector norms, team personality, relationship conflict

Questions about how to compose teams and coordinate member resources effectively are fundamental to team science. Scholars have focused on these team composition problems for over three-quarters of a century, and in that time have learned a great deal about the inherent complexity of

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the effects of member attribute distribution (e.g., Campion et al., 1993; Colbert et al., 2014; Guzzo & Shea, 1992; Humphrey et al., 2007; Jackson, 1991; Mathieu et al., 2014). Drawing much of this work together, Bell et al. (2018) specifically note the variation of member attributes both within and between team members, and more importantly, the need for tight alignment between theory and the operationalization of factors or attributes to make progress in understanding the effects of team composition. Our paper contributes to this effort in suggesting an additional approach for understanding the effects of attribute patterns in teams.

In particular, we note that researchers are becoming much more sophisticated in modeling attributes across a given set of team members (i.e., variable-centered approaches) and considering how attributes coalesce in relevant subgroups of team members (i.e., person-centered approaches) (see Howard & Hoffman, 2018). Variable-centered approaches allow researchers to isolate the effects of specific aggregate team member attributes, such as demographic characteristics (e.g., Horwitz & Horwitz, 2007; Williams & O'Reilly, 1998; van Knippenberg & Mell, 2016), personality traits (e.g., Barrick et al., 1998; Bell, 2007; LePine, 2003), or task-related abilities (e.g., Neuman & Wright, 1999; Stevens & Campion, 1999). Person-centered approaches recognize that teams and other collectives may contain multiple subgroups that can be characterized by various attributes (Morin et al., 2016) and thus consider the "clustering of people as opposed to variables" (Woo et al., 2018, p. 816). The variable-centered approach has dominated the team composition literature, but scholars are increasingly applying concepts from the person-centered approach to research on teams (e.g., Lee & Yoo, 2020; O'Neill et al., 2018).

This rise in a person-centered approach to team composition has led scholars to develop a new theory that considers the pattern of multiple attributes both within and across team members. However, to appropriately operationalize these theoretical arguments, empirical approaches are needed that can simultaneously consider unique levels of these attributes within and across each and every team member. For example, consider the attributes of optimism and assertiveness in Teams 1 and 2 in Table 1. The most optimistic member in Team 1 is also the least assertive member of the team, whereas the most optimistic member in Team 2 is the most assertive. Does it matter if a team's most optimistic member is also its most assertive? It seems reasonable to expect that it does since assertive team members often have disproportionate influence with their teammates (Pearsall & Ellis, 2006). Yet, it would be challenging to use existing variable-centered or person-centered approaches to fully address this hypothesis empirically.

Using a variable-centered approach, researchers would typically either: (a) focus on one team member attribute at a time, ignoring or controlling others (e.g., Barrick et al., 1998; LePine, 2003; Mohammed & Angell, 2003) or (b) consider the contingency effects of multiple attributes, but only after they are aggregated to the team level (e.g., Bradley et al., 2013; Homan et al., 2008). In our example, team optimism and assertiveness could be aggregated to the team level and then their independent or interactive effects on team outcomes could be considered. However, since these attributes have identical statistical distributions on these two teams, aggregating optimism, and assertiveness as means, standard deviations, or any other distribution property would not

Table 1. Patterns of Optimism and Assertiveness on two Organizational Teams.

Team 1 Members	Optimism	Assertiveness	Team 2 Members	Optimism	Assertiveness
Alice	5 out of 5	1 out of 5	Danielle	5 out of 5	4 out of 5
Betsy	3 out of 5	4 out of 5	Eric	3 out of 5	3 out of 5
Chris	2 out of 5	3 out of 5	Frances	2 out of 5	1 out of 5

differentiate them, despite differences in the pattern of these attributes within team members. Given individual behavior is a function of the interaction of multiple coexisting attributes (Moynihan & Peterson, 2001), the variable-centered approach struggles to fully account for the effects of team composition because it does not capture the pattern of multiple attributes coexisting within individual team members.

Alternatively, the person-centered approach focuses on the coexistence of multiple within-member attributes across the team. This approach is primarily designed to investigate subpopulations or subgroups within teams to determine how these subgroups affect relevant outcomes (Morin et al., 2016). Faultlines scholars, for example, explore how multiple team member attributes align to create the potential for subdivisions within a given team, and then relate the strength and distance between these subdivisions to outcomes such as team conflict and performance (Bezrukova et al., 2012; Lawrence & Zyphur, 2011; Thatcher et al., 2003; Woo et al., 2018). The challenge with this approach, however, is that it is limited when it comes to questions that transcend subgroups, particularly the pattern of multiple attributes outside of any subgroups. In the case of Teams 1 and 2, our research question does not involve subgroups, nor can these teams be meaningfully classified into subgroups based on optimism and assertiveness. Yet, the alignment of optimism and assertiveness clearly differs in these teams, and this difference has the potential to significantly affect team functioning.

To address such team composition questions that require a focus on the coexistence of multiple attributes, both within and across team members, we propose and demonstrate an *attribute alignment* approach. The attribute alignment approach provides scholars the opportunity to ask and answer new team composition questions. Besides variable-centered questions ("Does it matter *what* attributes a team has?") or person-centered questions ("Does it matter *what* subpopulations a team has?"), the attribute alignment approach allows researchers to ask, "Does it matter *who* on the team has which attributes?" As such, we propose an analytic technique for concurrently considering sets of member attributes in the context of each other, across the team, involving a geometrical definition of teams as matrices composed of individual members and their attributes. We believe this alignment approach complements both the variable-centered and person-centered approaches as an additional tool for operationalizing new research questions motivated by advances in team composition theory.

We make our case for the attribute alignment approach by providing a short summary of existing conceptualizations of team members' collective attributes. Then, we present our attribute alignment method and one example of when it is useful—in understanding how team members' personality traits align to affect team-level relationship conflict. Finally, we discuss broader theoretical and practical implications of the attribute alignment approach.

Current Approaches to Team Composition

Table 2 summarizes current approaches to team composition, highlighting their strengths and weaknesses. The table also suggests the theoretical questions they are best designed to answer and contains representative papers using each approach. We begin with variable-centered approaches to team composition. Variable-centered approaches use either additive or configurational aggregation models when considering team member attributes (Chan, 1998; Kozlowski & Klein, 2000; Waller et al., 2016). Additive models correspond to a "more is better" argument (or worse, depending on the attribute), suggesting that an attribute has a greater effect on teamwork when it exists at a greater magnitude within a given team (Mathieu et al., 2014). For instance, researchers may assume that a team will perform better if its members have higher cognitive ability. Yet, this approach assumes that team members are isomorphic, or that the contributions of their attributes to the team are proportionate and weighted equally (Bell et al., 2018). So, cognitive ability is assumed to be

Table 2. Three Approaches to Team Composition.

Approach	Theoretical premises	Methodological disadvantages	Typical research questions	Example operationalizations	Representative studies
Variable-centered: Focuses on detecting how distribution properties of certain attributes across team members affect teams.	This approach isolates the effects of specific variables by considering their magnitudes or distributions across team members. Often team members are assumed to be interchangeable (i.e., who possesses an attribute of interest does not matter as long as the attribute is present in the team).	This approach is not able to adequately address how multiple attributes within individuals manifest at the team level to influence team functioning. The effects of multiple attributes are considered only after they are first aggregated to the team level.	How does the general level of attributes within a team affect team functioning? For example, do teams with higher team levels of optimism and/or assertiveness perform better?	Mean of a given attribute across team members	Barrick et al. (1998), Bell (2007), Courtright et al. (2017), LePine (2003), Neuman et al. (1999), and Thiel et al. (2019)
			How does the pattern of attributes within a team affect team functioning? For example, do teams with one highly optimistic or one highly assertive member perform better?	Variance, min/max, skewness of an attribute across team members	Barrick et al. (1998), Barry & Stewart (1997), Bell et al. (2011), Mohammed & Angell (2003), and Neuman et al. (1999)
Person-centered: Clusters team members into subgroups based on patterns of their multiple attributes, and then examines how those subgroups affect teams.	This approach considers any number of within-person attributes to assign members to subgroups. It assumes that subgrouping plays a central role in explaining team functioning.	This approach is not able to adequately address attribute patterns that affect functioning independently of subgroups, such as their continuous alignment in some team members relative to others.	How does the extent to which teams are divided into subgroups based on a set of their attributes affect team functioning?	Thatcher's Fau; faultline distance	Bezrukova et al. (2012) (faultline distance) and Thatcher et al. (2003) (Thatcher's Fau)
			How does the extent to which teams are composed of different types of individual member profiles affect team functioning: for example, do teams composed mostly of	Latent class/profile analysis	Kollmann et al. (2009) and Marsh et al. (2009). **Although not primarily focused on teams, these papers demonstrate how to construct profiles of individuals within*

(continued)

Table 2. (continued)

Approach	Theoretical premises	Methodological disadvantages	Typical research questions	Example operationalizations	Representative studies
			one set of attributes (e.g., Class X) perform better than those composed mostly of a different set of attributes (e.g., Class Y)?		*collectives based on personal attributes.*
Attribute alignment: Focuses on how the pattern of team members' attributes, within members and across the team, affects teams.	This approach considers how any number of within-person attributes may coexist within team members across the team. It assumes that this pattern of attributes plays a central role in team functioning.	This approach is not well-suited to account for the influence of a single attribute across team members or specific predictions regarding subgrouping processes.	How does the coexistence of multiple attributes within team members, across the team, affect team functioning? For example, do teams whose optimistic members are also more assertive perform better than those whose optimistic members are less assertive?	Vector norm or vector angle	The current study

beneficial regardless of where that cognitive ability lies (i.e., which members are smarter), how it is distributed within the team, or what other traits are coupled with cognitive ability within team members. Therefore, additive models are useful in isolating relationships between general levels of attributes and team outcomes, a key step in understanding the nomological network of team attributes. However, additive models cannot identify the individual team members responsible for a particular effect or differentiate between team attribute patterns that produce the same mean (e.g., the two teams in Table 1).

Configurational models recognize that attributes may vary across team members, and that specific patterns of this variation may significantly affect team outcomes. They also recognize that the team-level expressions of member attributes may be qualitatively different when some members' attributes are weighted differently (Bell et al., 2018). As such, scholars taking this approach consider patterns of attributes at the team level, including their variability or the impact of one very high or very low scoring member on team processes or performance (e.g., Barrick et al., 1998; Ferguson & Peterson, 2015; Neuman et al., 1999). Thus, using a configurational approach, one may assume that one extremely intelligent member may drive a team to success, or one extremely unintelligent member may drive a team to failure, even if the teams have similar mean intelligence levels (Woolley et al., 2010). As such, configurational approaches are useful in identifying how specific patterns of a given attribute affect team outcomes. When examining multiple attributes, configurations are usually considered one variable at a time, across team members, rather than as covarying within team members. For example, a researcher may suggest a particular outcome when maximum scores of team optimism and assertiveness covary, which would not differentiate teams such as those in Table 1.

In sum, taking a variable-centered approach using additive or configurational aggregation models is useful and necessary for developing accurate nomological networks of team member attributes. Their main advantage over person-centered and alignment approaches (which we describe below) is their ability to identify specific drivers and outcomes of specific attributes. Variable-centered approaches provide evidence from which more complex theory can be developed, even if they do not fully address the complexity of individual team members. For instance, it would be very difficult to develop theory concerning how team member attributes coalesce without understanding the independent effects of each attribute. However, because the focus of the variable-centered approach is on combining single individual-level attributes across the team, for researchers to consider multiple attributes those attributes must first be aggregated to the team level and then considered jointly. In this sense, variable-centered approaches do not capture how attributes exist within team members, but instead how they exist within the team.

Recognizing "attribute interdependence" at the individual level (Lawrence & Zyphur, 2011), person-centered approaches allow researchers to consider multiple attributes within individuals, often to classify them into typological profiles that represent subpopulations of a given collective (Morin et al., 2016). In team composition research, this approach has most often been adopted to address compositional faultlines, which assess the likelihood a group will divide into smaller subgroups based on a combination of demographic characteristics, as well as how the distance between those subgroups affects team outcomes (e.g., Bezrukova et al., 2012; Lau & Murnighan, 1998). Thus, the person-centered approach is particularly effective in considering how subgroups form based on a wide variety of team members' attributes, which often explain why groups behave the way they do (e.g., Bezrukova et al., 2012; Choi & Sy, 2010; Li & Hambrick, 2005; Thatcher et al., 2003). A person-centered approach can be applied using a variety of statistical techniques (e.g., cluster analysis, latent class/profile analysis, latent class regression analysis, latent transition analysis, and growth mixture modeling; Muthén & Muthén, 2000; Woo et al., 2018) and is particularly useful for exploratory research (Morin et al., 2016).

However, a person-centered approach is not well-suited to address how multiple individual attributes influence group processes outside of assigning members to subgroups and exploring the influence of these subgroups on their teams. Once subgroups are determined, the person-centered approach fails to recognize continuity in the attributes that were used to assign team members to subgroups, which reduces the predictive power of the attributes themselves (Marsh et al., 2009). Additionally, the person-centered approach cannot account for the theoretical consideration of a single dominant team member. Often, a team member may possess a critical set of attributes compared to other teammates (Humphrey et al., 2009). For example, the alignment of intelligence and conscientiousness in one member relative to others may provide a clear task-planning role for that person within the team.

In summary, hypotheses that invoke multiple attributes *within and across team members* cannot be fully tested using existing approaches. To address this, we turn to the open systems perspective articulated by Arrow et al. (2000) and Kozlowski and Klein (2000), who provide the theoretical grounding for considering the concurrent and varying levels of individual attributes within individuals across the team. We label this method the *attribute alignment approach*.

The Attribute Alignment Approach to Team Composition

The open systems perspective recognizes teams as "open and complex systems that interact with the smaller systems (i.e., individual members) embedded within them and the larger systems (e.g., organizations) within which they are embedded" (Arrow et al., 2000, p. 34). Drawing from this perspective, we propose that scholars revisit the complexity of the core element of teams: individual members themselves. Team members are complex systems of thoughts, emotions, and behaviors that coalesce to produce higher-level motivations, attitudes, and actions. These systems and their attributes coexist in teams and influence each other.

As such, to better understand the complexity of team composition, researchers need to consider team members as systems, composed of local attributes, in addition to considering teams as global contexts composed of members. This requires a focus on individual team members as complex entities composed of multiple attributes that comprise the larger team (Emich & Lu, 2017). The core argument of our attribute alignment framework is that *considering multiple team member attributes, in the context of each other and across the team, can generate significant insight into team processes and outcomes*.

In this approach, *alignment* means teams are composed of members who are relatively high on two (or more) focal attributes and other members who are relatively low on those attributes (e.g., team members who are optimistic are also assertive, while other members who are not optimistic are also not assertive). *Unalignment* then means that teams are comprised of members who are relatively low on one attribute but high on a second attribute and members who are relatively high on the first attribute but low on the second (e.g., team members who are optimistic are not assertive and assertive members are not optimistic). Finally, when there is neither alignment nor unalignment, there is *misalignment*, which reflects no discernable relationship between attributes within team members across the team. With extreme cases of alignment or unalignment, we may observe subgroups, for instance with one subgroup containing members who score high on attributes of interest and another subgroup containing members who score low on attributes of interest. Yet, alignment or unalignment also allows for a continuous view of attributes across team members, even if meaningful subgroups do not exist. This can occur in any number of cases, for example, in Table 1, where one team member scores high on the attributes of interest, another team member scores low on these attributes, and a third member scores moderately, making subgroup assignments unclear or irrelevant, despite the overall presence of attribute alignment. For this reason, the attribute alignment approach is especially suited to address the alignment of variables measured on continuous scales, such as personality traits or cognitive ability, rather than categorical attributes such as demographic variables, although such variables can be accounted for mathematically.

Theoretically, alignment allows researchers to consider the effects of patterns of different attributes within team members while simultaneously considering their relative existence across team members. Empirically, the degree to which attributes align within a team can be examined by construing teams as matrices composed of individual members and their attributes and then comparing the resultant attribute vectors. These differences can then be compared across teams.

Viewing Teams as Matrices

To support the premise that teams are complex systems composed of members who are equally complex, empirically teams must be conceptualized as sets of members who themselves have multiple attributes and belong to an overarching collective. To do this, we geometrically interpret teams in an i by j matrix where i is the number of team members and j is the number of team member attributes considered. First, we arrange the set of team members' observed attributes into vectors. Going back to Table 1, each team has an optimism vector and an assertiveness vector (and many other vectors which are unobserved in this data set). These are ordered, keeping the team members themselves consistent. Below, we describe the optimism and assertiveness of Teams 1 and 2's members, from Table 1, as vectors:

$$\text{Team 1: Optimism: } \boldsymbol{a}_{11} = \begin{pmatrix} 5 \\ 3 \\ 2 \end{pmatrix}, \quad \text{Assertiveness: } \boldsymbol{a}_{12} = \begin{pmatrix} 1 \\ 4 \\ 3 \end{pmatrix}$$

$$\text{Team 2: Optimism: } \boldsymbol{a}_{21} = \begin{pmatrix} 5 \\ 3 \\ 2 \end{pmatrix}, \quad \text{Assertiveness: } \boldsymbol{a}_{22} = \begin{pmatrix} 4 \\ 3 \\ 1 \end{pmatrix}$$

In these expressions, $\boldsymbol{a}_{11}$ indicates the first attribute of the first team, in this case optimism of the team's members. Team members' attributes are then listed down the column of the vector. Combining $\boldsymbol{a}_1$ vectors creates a team attribute matrix. The order in which elements appear is immaterial, so long as it is consistent across vectors. That consistency demands that the same individual populates the same index in all vectors.[1] In this way, researchers can arrange any individual-level attributes they measure into vectors and arrange those vectors into a team matrix. Once teams are geometrically interpreted into matrices, researchers can leverage any number of geometric analytic techniques to tackle individual complexity within teams. As representative examples, we will describe the use of vector norm and vector angle to assess attribute alignment. To do this in a well-structured and rigorous manner, however, researchers should first consider two conceptual assumptions when constructing an alignment measure: symmetry and permutation invariance between attributes or vectors.

Symmetry and Permutation Invariance Between Attributes. Symmetry addresses how to order team members when considering the alignment of their attributes. Permutation invariance between attributes addresses the relative influence of each member and attribute on the alignment score. We denote a team-level feature, K, the alignment of two attributes for a team with d members, using the following notation: $K(\boldsymbol{x}, \boldsymbol{z})$: $\mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$. Here, x and z are the d-length vectors containing the team member attribute values for two distinct attributes (e.g., x for optimism and z for assertiveness). We use the notation x_i for $1 \leq i \leq d$ to denote the ith element of the vector, which contains the attribute value for the ith team member. We assume, to simplify our discussion, that the vectors (attributes) only contain nonnegative values. However, alignment computations can also be defined in situations where negative attribute values exist.

Team attribute alignment, K, can be defined in infinitely many ways once a matrix structure is established. That said, for practical purposes, we propose considerations based on symmetry and permutation invariance for any operationalization of team attribute alignment[2]:

- Symmetry: $K(x, z) = K(z, x)$. This requires that there is no distinction between asking "How do x and z align to influence team performance?" and "How do z and x align to influence team performance?" Thus both attributes contribute to the alignment value in the same way, with no preference given to either attribute.
- Permutation invariance: $K(Px,\ Pz) = K(x,\ z)$, for any P, a $d \times d$ permutation matrix exists (shuffling of the rows of the identity matrix). This requires that there be no preferred ordering of team members (any ordering is arbitrary). Any distinction between the different roles that team members have is discarded during the alignment computation. However, this may be accounted for in an auxiliary attribute column.

In this article, we always respect these symmetry and permutation invariance properties. However, these conditions may be relaxed given particular theoretical guidance. For example, one might prefer to account for the role of leadership in a team by weighting the alignment between the leader's attributes more heavily than that of other members. In this case, there is a preferred ordering and weighting of team members, relaxing permutation invariance. This practice would be consistent with work finding, for example, that leaders have a disproportionate influence on the collective efficacy and psychological safety of their teams (Chen & Bliese, 2002; Edmondson, 1999; Edmondson & Lei, 2014; Watson et al., 2001).

In addition to respecting symmetry and permutation invariance, researchers may also consider the relative influence of each attribute on a given alignment score. To interpret the vector norm as an alignment score based on equal contribution from two attributes, those attributes must have the same variance (Bodner, 2018). If variances are not equal, the attribute with more variance will account for a larger portion of the attribute alignment value. In this case, researchers may attempt a transformation to produce more equal variances in their attributes of interest. Square root, natural log, linear, and reciprocal transformations often work well for this purpose. However, if equal variances cannot be achieved, or attributes exist on nonfinite scales making standardization difficult or meaningless, researchers may instead calculate vector angle as a measurement of alignment (described below).

Defining Two-Attribute Alignment Using Vector Norm. To measure alignment between two attributes in a team, the most parsimonious metric that satisfies our stated conditions (symmetry and permutation invariance) is the p-norm between two vectors, defined as follows:

$$\|x - z\|_p = \left(\sum_{i=1}^{d} |x_i - z_i|^p\right)^{1/p} \tag{1}$$

When $p = 2$, this formula recovers the Euclidean distance between two vectors. One property of the p-norm is that larger values of p yield norms which are more strongly influenced by only the larger differences between x and z. For example, at $p = \infty$, this norm is defined as the largest entry in the vector in absolute value, ignoring all other differences in attributes besides those of the least aligned member. In contrast, smaller values of p more uniformly value contributions irrespective of their magnitude, allowing all member alignments to contribute to a team attribute alignment value. The 2-norm represents a generally accepted variant accounting for alignment among all members. In other words, because the only way that $\|a_1 - a_2\|_p = 0$ is if $a_{1,i} = a_{2,i}$ for $1 \leq i \leq d$, the 2-norm provides a more holistic view of the similarities and differences between two attributes. For this reason, we recommend using $p = 2$ to calculate two-attribute alignment. Based on this reasoning, the foundational element in defining a two-attribute alignment feature is the distance between vectors x and z, defined as follows:

$$K(x, z) = \|x - z\|_2 = \sqrt{(x_1 - z_1)^2 + \ldots + (x_d - z_d)^2} = \left(\sum_{i=1}^{d} |x_i - z_i|^2 \right)^{1/2} \tag{2}$$

This distance feature has the benefit of being the simplest in terms of the higher-order interactions required: only second-order interactions between x_i and x_j are required to compute $||x - z||_2^2$ (Harrison & Klein, 2007). The square root term is applied so that $K(x, z)$ is on the same order as x. Note that the only circumstance where $K(x, z) = 0$ is for $x = z$, that is, every team member reports the same values for both attributes. We extrapolate the full logic behind the advantages of using vector norm to consider attribute alignment, as opposed to more complex models including linear models of individual attributes, in Appendix A.

The idea of using distance as a feature is not new, though the use of these features in building linear models is a relatively recent adoption in the teams' literature (e.g., Lau & Murnighan, 1998; Meyer & Glenz, 2013; Thatcher et al., 2003). For example, when calculating the *Fau* statistic, researchers quantify diversity faultline strength as the squared difference between the mean attributes of potential subgroups "delivering the largest ratio of between subgroup variance over the total group variance of attributes" (Meyer & Glenz, 2013, p. 398). In this calculation, researchers consider the Euclidean distance between mean subgroup attributes, although not necessarily with a geometric motivation. Instead, we embrace the geometric nature of this traditional calculation to more clearly define team member attributes as they are observed and to describe differences across attributes within individual members by comparing the resultant vectors.

Accounting for Differences in Team Size and Attribute Measurement. Researchers may want to jointly study and model teams of different sizes. However, formula (2) provides larger teams more opportunity to accumulate unalignment than smaller teams, since each additional member has the potential to increase the value of $||x - z||_2$. To account for the different d values of different teams, we modify our attribute alignment calculation to the following, *which is the final formula we recommend for measuring two-attribute alignment using vector norm*:

$$K(x, z) = \|x - z\|_2 \, / \, \sqrt{d} \tag{3}$$

This rescaling ensures that the maximum distance between vectors x and z is equal for different-sized teams. As an example, if x were a d-dimensional vector of all zeros and z were a d-dimensional vector of all ones, then $K(x, z) = 1$ for all values of d. This correction normalizes the most extreme outcomes and reduces the significance of deviations of individual members in large teams.

However, we should note that since this correction forces teams to have the same maximum unalignment, larger teams have more precision in defining small unalignments. For example, consider a case where both x and z are vectors with all zeros, except in the first entry where z has the value of 1. In this situation, $K(x, z) = 1 \, / \, \sqrt{d}$, meaning that differences of the same absolute magnitude are less significant on larger teams. For instance, on a four-person team, the minimum unalignment for a given set of two attributes, measured in integers, would be one-half (or 1 over the square root of 4) using this correction, while the minimum unalignment on a nine-person team would be one-third. This is only relevant when only one member of a given team is unaligned to the minimum degree, for example, integer attribute vectors of (3, 3, 3, 4) versus (3, 3, 3, 3), so the team as a whole is highly aligned. However, alternatively, a researcher may be interested in a consistent minimum unalignment. In that case, one person out of alignment will contribute the same unalignment to a four-person team as to a nine-person team (or any other size team). The base form of the distance (without the $1 / \sqrt{d}$ rescaling; formula [2]) accomplishes this.

In essence, researchers must choose whether they want to: (a) equate unalignment between teams (e.g., assume that two unaligned members on a four-person team is equivalent to two equally unaligned members on a nine-person team, or that no number of aligned members will account for the unalignment of a few) and hence use formula (2) or (b) use formula (3) and equalize alignment scores between teams of different size (e.g., assume that having two unaligned members on a team of four should account for more unalignment than having two equally unaligned members in a team of nine). Although in some instances researchers may only be interested in general unalignment regardless of team size, we expect most researchers will prefer the $1 / \sqrt{d}$ transformation rescaling to equate the alignment of teams of different sizes.

Vector Norm Visualization. In this section, we provide an example visualization of how attribute alignment is calculated using vector norm to aid in its interpretability and to emphasize its practicality. Using the 2-norm as defined above in formula (3), the dissimilarity between the optimism and assertiveness of the members of Team 1 in Table 1 is defined as follows:

$$K\left(\begin{pmatrix}5\\3\\2\end{pmatrix},\begin{pmatrix}1\\4\\3\end{pmatrix}\right)=\frac{1}{\sqrt{d}}\left\|\begin{pmatrix}5\\3\\2\end{pmatrix}-\begin{pmatrix}1\\4\\3\end{pmatrix}\right\|_2$$

$$=\frac{\sqrt{(5-1)^2+(3-4)^2+(2-3)^2}}{\sqrt{3}}$$

$$=\frac{\sqrt{16+1+1}}{\sqrt{3}}=\sqrt{6}\approx 2.45$$

Whereas the means and variances of optimism and assertiveness are identical between Teams 1 and 2 (as well as all other distribution properties), they are different in terms of the alignment of their optimism and assertiveness vectors. The vector norm between Team 1's optimism and assertiveness is about 2.45, while the vector norm between Team 2's attributes is about .82, which means that optimism and assertiveness align to a greater degree in Team 2 than in Team 1.

Figure 1 provides a visualization of attribute alignment using the vectors derived from Table 1. Each team has its own multidimensional space (since alignment between vectors is analyzed for each team, respectively). Within each space (or team), each axis represents one team member (e.g., Alice, Betsy, or Chris on Team 1) so that the number of dimensions is equal to the number of members on a given team. Then team members' attributes, represented as vectors, are mapped to each axis, for example, (Alice_{O}[5], Betsy_{O}[3], and Chris_{O}[2]) and (Alice_{A}[1], Betsy_{A}[4], and Chris_{A}[3]). Each vector corresponds to a point in this three-dimensional space (e.g., TEAM_{O} and TEAM_{A}), and the distance between these two points represents the extent to which these two within-person attributes align across the team as a whole. The smaller the distance, the greater the alignment of these two attributes. Figure 1 shows that the distance between the attributes of Team 1's members is greater than the distance between the attributes of Team 2's members, or that optimism and assertiveness align to a greater degree in Team 2.

Once the vector norm is calculated, its relationship to other team-level properties can be tested. For example, the vector norm and a key team outcome variable (e.g., team performance) both exist at the team level, so their relationship could be assessed by conducting a standard linear regression where performance is regressed onto teams' optimism-assertiveness vector norms. A negative relationship between these optimism-assertiveness vector norms and team performance would indicate that as optimism and assertiveness align more teams perform better, since a lower vector norm indicates greater attribute alignment.

Here, it is important to note that empirical attribute alignment values are only meaningful relatively—when being compared across teams and related to team-level outcomes of interest. In other words, it is not meaningful to state that a certain vector norm value represents low, medium, or high alignment without considering other values in the same dataset. In isolation, the alignment score of a single team is not meaningful; however, it is meaningful to know that Team 1 is less aligned on a given set of attributes than Team 2. This is consistent with several other team composition approaches such as those considering subgroup strength and distance.

Defining Two-Attribute Alignment Using Vector Angle. In certain instances, researchers may need to address research questions that involve attributes with unequal variances, or that cannot be easily transformed. One advantage of our geometric interpretation of team member attributes is that it provides researchers the opportunity to develop methods to address such issues. In this case, we suggest using an alternate version of the distance feature to calculate the angle between the vectors x and z, computed as follows:

$$K_{\text{angle}}(x, z) = \cos^{-1}\left(\frac{x^{\mathrm{T}}z}{||x||_2||z||_2}\right) \tag{4}$$

where $x^{\mathrm{T}}z$ is the inner product between x and z. For x and z taking only nonnegative values, this quantity is bounded within $[0, \pi / 2]$. This feature is ill-defined when an attribute takes all 0 values (since we would be computing the angle of a vector with respect to a point), so at least one value in each attribute must be nonzero.

In this way, although the concept of distance being the "simplest" feature can still be applied, vector angle addresses vector direction over vector magnitude. For example, the economics and strategy literatures use the cosine between vectors to assess the similarity between firm patent portfolios, termed technological distance (Kay et al., 2014; Peretto & Smulders, 2002). The cosine allows a comparison of the patent portfolios of large and small firms (Peretto & Smulders, 2002), such as a firm having two patents in carbon chemistry, five in magnetics, and three involving miscellaneous consumer goods; and a firm having 200, 500, and 300, respectively. Using the angle between these vectors ([2, 5, 3] and [200, 500, 300]) allows for comparison between the firms despite their size differences—in this case recognizing their portfolio distributions are the same. The maximum possible K_{angle} value occurs when the vectors point in orthogonal directions, such as $x = (1, 0, 3)$ and $z = (0, 4, 0)$. This is logically consistent with the idea that team attribute alignment is meant to take high values when the vectors have little in common. Still, we consider this attribute alignment measure secondary to calculating vector norm because vector angle does not differentiate between the magnitudes of team member attributes, and most previous theoretical work is built on considering attribute magnitudes.

The Case of Neuroticism, Agreeableness, and Relationship Conflict

To provide one example of the applicability of the attribute alignment approach, we present a case in which we examine how team member neuroticism and agreeableness, two of the traits in the five-factor model of personality (Costa & McCrae, 2008), align to influence team relationship conflict. The association between personality attributes and conflict has been well documented (e.g., Barrick et al., 1998; Bono et al., 2002; Bradley et al., 2013), providing a helpful benchmark from which to highlight the additional insights that alignment can provide in understanding the effects of personality composition on team functioning. Of the Big Five, neuroticism, or the tendency toward negative affect including excessive worrying, feelings of distress, and generally negative views of the world (Costa & McCrae, 2008; Suls et al., 1998), and agreeableness, or the extent to which individuals are cooperative, trusting, and concerned about getting along with others (Costa & McCrae, 2008; Suls et al., 1998), have been the most consistently linked to relationship conflict, which is the extent to which there is a state of discord due to personal incompatibilities among team members (de Wit et al., 2012; Jehn, 1995; Jehn et al., 1999).

The relationships between these personality attributes and conflict have traditionally been addressed from a variable-centered perspective, which has shown that higher mean levels of neuroticism typically increase team conflict and higher mean levels of agreeableness typically decrease it (Barrick et al., 1998; Graziano et al., 1996), while findings concerning configurational patterns of these attributes are mixed (e.g., Barrick et al., 1998; Bono et al., 2002; Poling et al., 2006). Here, we use a field sample of master of business administration (MBA) consulting teams to test how the theoretical insights associated with the person-centered and attribute alignment approach compare to this traditional variable-centered perspective when considering neuroticism and agreeableness. To test the variable-centered approach, we ask whether teams with higher or lower mean levels of neuroticism and agreeableness experience more relationship conflict (additive) and whether having one member with extremely high or low levels of these attributes, causes their team to experience more relationship conflict (configurational). To test the person-centered approach, we ask whether the tendency for a team to split into subgroups based on these attributes, and the distance between these subgroups, affects relationship conflict. Finally, to test the attribute alignment approach, we ask whether neuroticism-agreeableness alignment matters in predicting the existence of team relationship conflict.

Participants and Procedure

Our sample comes from an ongoing data collection effort to examine team composition and outcomes among MBA students at a graduate business school in the United Kingdom. Our sample includes 610 individuals assigned to 92 teams of between five and eight members ($M = 6.63$, $SD = .60$). Individuals were assigned to teams to maximize diversity in functional expertise and nationality. They represented 64 countries, led by the United States (103), India (68), and the United Kingdom (65), and 467 companies across 16 industries. Their average age was 28.41 years ($SD = 2.33$), 76% were male, and they had an average work experience of 5.55 years ($SD = 2.07$). Teams were assigned at the start of the student's first academic term in the MBA program and remained intact for one calendar year. Students completed all group project work across courses in these assigned teams.

Prior to beginning the MBA program, students provided data on individual personality, including our attributes of interest. We collected our relationship conflict measure after the first week of the academic term, during which the teams work intensively together on interdependent tasks in a leadership course, including drafting a team charter and completing a strategic decision-making simulation.

Measures

Neuroticism and Agreeableness. We measured agreeableness and neuroticism using the 240-item NEO-PIR Inventory (McCrae & Costa, 2010) of which 48 items measured both agreeableness ($\alpha = .85$) and neuroticism ($\alpha = .92$). Responses were indicated on a five-point Likert-type scale from "*Strongly Disagree*" to "*Strongly Agree*."

Relationship Conflict. We measured relationship conflict using four items from Jehn (1995) and Behfar et al. (2011) assessing interpersonal friction among team members (i.e., relationship conflict) ($\alpha = .95$). Responses were indicated on a seven-point Likert-type scale from "*Never, None, Not at*

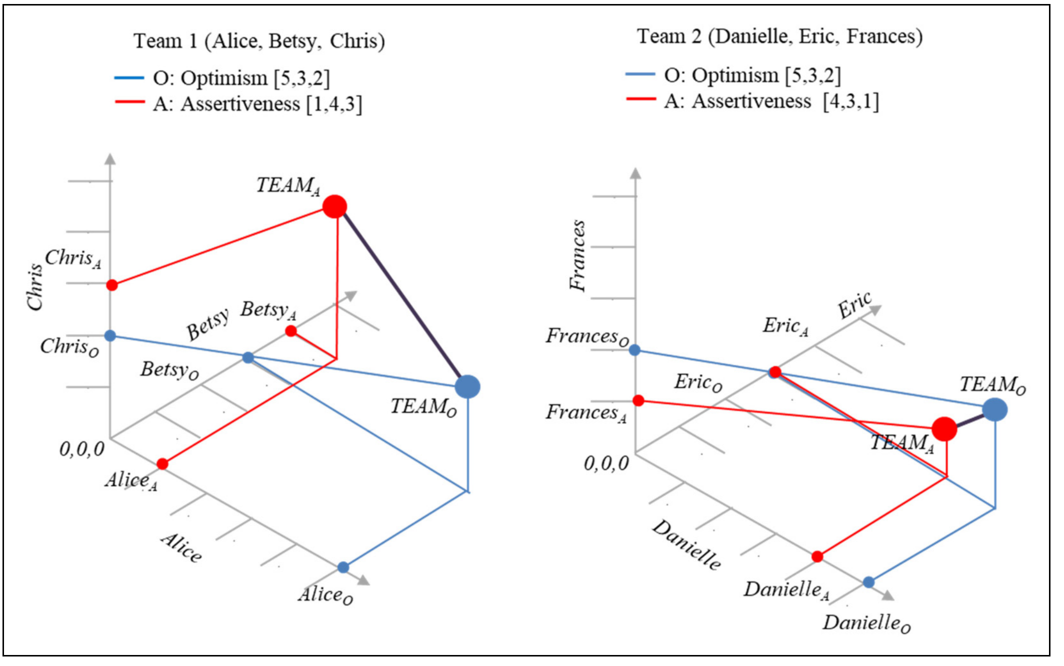

Figure 1. Vector mapping of member attributes in Table 1. The purple (or darker) line connecting the large red and blue dots indicates vector norms.

All" to "*Constantly, Always, Totally*." We used the mean among team members as our measure of team relationship conflict (ICC1 = .49, ICC2 = .92, rwg = .86, *SD* = .20).

Class Year (Control). We controlled for class year (i.e., dummy coded) because there were two cohorts in this study.

Aggregation

Variable-Centered Aggregation. Following previous literature (e.g., Barrick et al., 1998), we assessed both additive and configurational variable-centered approaches by calculating the means, minimums, and maximums of neuroticism and agreeableness within each team.

Person-Centered Aggregation. Following Thatcher et al. (2003), we calculated the tendency for teams to split into two homogenous subgroups based on neuroticism and agreeableness using the *Fau* statistic. Additionally, following Bezrukova et al. (2012) and Meyer and Glenz (2013), we calculated the distance between subgroups, as adapted from the clustering literature, as the Euclidian distance between subgroup centroids, that is, between the average scores of these attributes within each subgroup.

Attribute Alignment Aggregation. We calculated the alignment of neuroticism and agreeableness by creating a program in Python 3.5. We provide this code, in Python 3.5, and equivalent code in R 4.0.5, in Appendices B and C, respectively. First, we tested whether agreeableness and neuroticism had equal variance in our sample. Levene's test indicated unequal variances ($F = 45.60$, $p < .01$), such that agreeableness had less variance ($SD = .323$) than neuroticism ($SD = .446$). To address this difference, we conducted a linear transformation on the agreeableness scores by multiplying them by the ratio of this difference (1.38) before calculating alignment. This resulted in equal variances between the attributes ($F = .12$, $p = .73$). Then, we calculated the vector norm between team members' neuroticism and agreeableness using the following formula (N = neuroticism, A = agreeableness), where d varied between five and eight:

$$K(N, A) = \frac{1}{\sqrt{d}}\sqrt{(N_1 - A_1)^2 + \ldots + (N_d - A_d)^2}$$

Results and Discussion

We report descriptive statistics and correlations between individual and team-level neuroticism, agreeableness, and relationship conflict in Table 3. Note that alignment does not significantly correlate with either faultline strength, measured by the *Fau* statistic, or faultline distance, despite their similar mathematical underpinnings based in Euclidian geometry. This adds credence to the unique applicability of the attribute alignment approach.

Results of a series of linear regressions are presented in Table 4. First, we explored whether a team's mean level of neuroticism and agreeableness or their interaction term influenced team relationship conflict. Consistent with previous work (Barrick et al., 1998), model 1 indicates that teams with higher mean levels of neuroticism have more relationship conflict, while teams with higher mean levels of agreeableness have less relationship conflict. Model 2 indicates that their interaction does not influence relationship conflict.

Next, we tested alternative distribution properties (i.e., minimum and maximum) and their interaction terms. Considering maximum scores of both attributes is consistent with the conceptual argument that having one member who scores high on neuroticism and one member who scores high on agreeableness has a significant effect on team conflict, regardless of whether these maximums occur in the same individual. Minimum scores emphasize the contribution of the lowest scoring member with respect to these attributes. Model 3 shows, also consistent with previous work (Barrick et al., 1998), that minimum neuroticism has a strong positive effect on team relationship conflict. This indicates that having at least one calming emotionally stable member (i.e., low neuroticism) in a team can help reduce relationship conflict. Models 4 through 6 indicate that the interaction between minimum neuroticism and agreeableness, as well as maximum scores and their interactions, do not influence team relationship conflict.

We also considered a person-centered approach focused on faultline strength and distance. Although subgrouping based on demographic characteristics has been shown to produce team conflict (Jehn et al., 2008), our findings indicate that subgrouping based on personality characteristics, specifically neuroticism and agreeableness, does not affect relationship conflict (most likely because these attributes are not immediately visible and thus do not spur automatic social categorization processes; van Knippenberg & Schippers, 2007). Models 7 and 8 show no relationship between either faultline strength or distance and relationship conflict.

The lack of support for any contingency effects between neuroticism and agreeableness at the team level (whether considered additively as means or configurationally as minimums and maximums) or subgrouping effects based on these variables, seems to indicate that these attributes affect team relationship conflict independently. Yet, considering the alignment of neuroticism and agreeableness within individuals across the team can lend further insight into these findings. Model 9 reveals that, by itself, the alignment of neuroticism and agreeableness accounts for 20% of the variance in team relationship conflict, see Table 5. The negative coefficient for alignment indicates that when there is less distance between neuroticism and agreeableness, that is, when these two traits align to a greater degree, teams experience more relationship conflict. Conceptually, this means that teams with members who score relatively high on neuroticism and agreeableness as well as those who score relatively low on neuroticism and agreeableness experience more relationship conflict than teams with members whose neuroticism and agreeableness do not align (e.g., the members who score high on neuroticism score low on agreeableness and vice versa).

Although variable-centered and alignment approaches may be used for different theoretical reasons (see Table 2), we further report models including multiple approaches to show their similarities and differences in predicting team relationship conflict in Table 5. Models 10 and 11 show that including previously significant additive and configurational conceptualizations of team member neuroticism and agreeableness to our alignment model does not significantly increase its predictability. Still, although mean levels of neuroticism and agreeableness accounted for 15% of the variance in relationship conflict (see model 1), affirming the utility of traditional variable-centered additive approaches, considering neuroticism-agreeableness alignment significantly increases the predictive power of that model (model 1 vs. model 10; $\Delta R^2 = .05$, $\Delta F(1,87) = 5.81$, $p = .02$). Adding neuroticism-agreeableness alignment to model 3 has a similar effect ($\Delta R^2 = .09$, $\Delta F(1,87) = 10.09$, $p < .01$). Finally, models 12 and 13 show that even when controlling for subgrouping tendencies, neuroticism-agreeableness alignment significantly influences team relationship conflict.

These findings are practically and theoretically significant. They demonstrate how considering the pattern of attributes within and across team members has the potential to predict an important team outcome over and above their variable-centered and person-centered consideration. Here, we find that the alignment of neuroticism and agreeableness predicts a large amount of variance in team relationship conflict, in addition to our replication of previous findings regarding the effects of mean and minimum levels of these variables.

Theoretically, this pattern of neuroticism-agreeableness alignment may affect relationship conflict because team members with high scores on both neuroticism and agreeableness will be hypersensitive to, as well as concerned about, interpersonal and noninterpersonal problems (Suls et al., 1998); whereas team members with low scores on neuroticism and agreeableness are not likely to share these concerns, nor are they particularly motivated to be cooperative. We hypothesize that relationship conflict ensues because members whose high neuroticism coexists with high agreeableness are likely to worry about the degree to which their team is getting along and are quick to raise the issues that concern them. At the same time, members with low levels of neuroticism and agreeableness are unable or unwilling to address their teammates' concerns, triggering further worry and distress. In contrast, when these attributes are unaligned, members with high neuroticism and low agreeableness may be difficult to engage constructively because they are hypersensitive yet unconcerned with maintaining relationships. However, their teammates with low neuroticism and high agreeableness are likely to be motivated to cooperate in the interests of preserving interpersonal relationships for their own sake, even where they do not share the same sensitivity, effectively mitigating team relationship conflict.

General Discussion

The attribute alignment approach has the potential to generate significant insight into team effectiveness by allowing researchers to revisit and extend team composition theory. Our approach construes teams as matrices that can be analyzed and interpreted geometrically, consistent with the proposition that teams are complex systems composed of members who each have an array of attributes, and whose attribute alignment influences team-level functioning. Along with the variable-centered approach, which helps build the nomological network of the effects of specific attributes on team functioning, and the person-centered approach, which considers the effects of subgroups derived from multiple within-person attributes, the attribute alignment approach allows for the consideration of multiple attributes both within and between team members.

We also demonstrate the usefulness of our method to test how patterns of within-person attributes can influence important team outcomes by looking at a field sample of teams where we find that the alignment of neuroticism and agreeableness affects team relationship conflict. Importantly, this alignment predicts significant variance in relationship conflict over and above other ways of operationalizing these same team composition attributes (e.g., mean levels, minimum/maximum levels, and

Table 3. Means, Standard Deviations, and Correlations Among Focal Team-Level Variables.

Variable	Mean	*SD*	1	2	3	4	5	6	7	8	9
1. Team N mean	2.58	0.18	—								
2. Team A mean	3.38	0.13	−0.25*	—							
3. Team N minimum	2.04	0.26	0.63**	−0.18	—						
4. Team A minimum	2.97	0.25	−0.21	0.58**	−0.03	—					
5. Team N maximum	3.17	0.35	0.61**	−0.12	0.11	−0.23*	—				
6. Team A maximum	3.77	0.23	−0.07	0.64**	−0.11	0.08	0.13	—			
7. Team N–A *Fau*	0.67	0.11	−0.01	−0.02	0.00	0.16	0.05	−0.16	—		
8. Team N–A faultline distance	0.61	0.27	0.15	0.01	−0.23*	−0.29**	0.58**	0.26*	0.58**	—	
9. Team N–A vector norm	0.92	0.14	−0.63**	0.55**	−0.49**	0.29**	−0.33**	0.32**	0.17	0.19	—
10. Team relationship conflict	2.71	0.81	0.27**	−0.29**	0.26*	−0.10	0.08	−0.09	−0.12	−0.07	−0.42**

Note. N = Neuroticism; A = Agreeableness. $^{*}p < .05$. $^{**}p < .01$.

Table 4. The Impact of Team Neuroticism and Team Agreeableness on Team Relationship Conflict (Variable-Centered and Person-Centered Approaches).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	−529.59 (322.37)	−523.02 (324.77)	−628.80 (324.57)	−610.87 (325.39)	−648.11 (339.12)	−648.77 (341.44)	−664.78 (331.92)*	−666.72 (334.71)*
Class year	.27 (.16)	.26 (.16)	.31 (.16)	.31 (.16)	.32 (.17)	.33 (.17)	.33 (.17)*	.33 (.17)*
Team N mean	.97 (.46)*	1.06 (.56)						
Team A mean	−1.28 (.64)*	−1.20 (.69)						
Team N minimum			.80 (.32)*	−3.62 (4.77)				
Team A minimum			−.23 (.32)	−3.30 (3.32)				
Team N maximum					.20 (.24)	.37 (3.98)		
Team A maximum					−.24 (.38)	−.11 (3.37)		
Team N mean × Team A mean		−.02 (.06)						
Team N min × Team A min				1.49 (1.60)				
Team N max × Team A max						−.04 (1.05)		
Fau (faultline strength)							−.79 (.75)	
Faultline distance								−.14 (.31)
F	5.24**	3.91**	3.84*	3.09*	1.74	1.29	2.68	2.22
R^2	0.15	0.15	0.12	0.13	0.06	0.06	0.06	0.05

*$p < .05$. ** $p < .01$.
Note. DV = team relationship conflict in all models; N = neuroticism; A = agreeableness. Unstandardized coefficients and their standard errors are presented.

subgrouping tendency), clearly demonstrating that the within- and between-person pattern of these traits matters when it comes to the experience of team relationship conflict. Our empirical example also demonstrates that an attribute alignment approach can be used by itself to answer a research question of interest (e.g., model 9 in Table 5), or conjointly with other approaches to test different hypotheses concerning team outcomes. For example, if mean levels of a particular attribute or set of attributes predict team performance above their alignment or a subgrouping metric, an additive explanation of the effect of that attribute on team performance is appropriate. Alternatively, if the *Fau* statistic were the only one related to an outcome of interest, it would indicate that subgroups meaningfully form based on the combination of the attributes in question, as opposed to their general coexistence across the team, which significantly influence that outcome.

Theoretical and Practical Implications

Beyond demonstrating the usefulness of the attribute alignment approach for team composition research, our empirical example reveals larger theoretical contributions that can be made to different literatures. For example, in our demonstration of the attribute alignment approach, we make contributions to both the literature on personality (e.g., Barrick et al., 1998; Bell, 2007) and team conflict (de Wit et al., 2012; Jehn, 1995). We achieve this by employing a method that captures the

Table 5. The Impact of Team Neuroticism and Team Agreeableness on Team Relationship Conflict (Attribute Alignment Approach).

Variables	Model 9	Model 10	Model 11	Model 12	Model 13
Intercept	−537.45 (306.93)	−513.60 (313.97)	−572.84 (316.08)	−532.99 (308.46)	−543.18 (309.53)
Class year	.27 (.15)	.26 (.16)	.29 (.16)	.27 (.15)	.27 (.15)
Team N mean		.14 (.57)			
Team A mean		−.39 (.73)			
Team N minimum			.22 (.35)		
Team A minimum			.06 (.33)		
Team N maximum			−.17 (.25)		
Team A maximum			−.30 (.38)		
Team N mean × team A mean					
Team N min × team A min					
Team N max × team A max					
Fau (faultline strength)				−.32 (.71)	
Faultline distance					.07 (.29)
Team N–A vector norm	−2.29 (.55)**	−1.98 (.82)*	−2.40 (.74)**	−2.25 (.56)**	−2.31 (.56)**
F	11.24**	5.60**	3.90**	7.50**	7.43**
R^2	0.20	0.21	0.22	0.20	0.20

$^{*}p < .05$. $^{**}p < .01$.

Note. DV = team relationship conflict in all models. N = neuroticism. A = agreeableness. Unstandardized coefficients and their standard errors are presented.

complexity of individual team members (e.g., Kozlowski & Klein, 2000; Mathieu et al., 2019) and answers previous calls to explore the microdynamics and patterned nature of team composition (Crawford & LePine, 2013; Humphrey & Aime, 2014) by better pairing team composition theory with commensurate operationalizations (Bell et al., 2018). It also answers recent calls to better understand the microfoundations of team conflict (Shah et al., 2021).

Our method also has significant practical applications for organizational teams. Because team members are complex, managers often tend to rely on instinct when composing teams that research suggests largely focuses on homophily (e.g., Williams & O'Reilly, 1998). Using alignment data would allow managers to be more evidence-based and precise when building teams considering the inherent complexity of individual team members. Using the attribute alignment approach could also help managers when they appoint individuals to an existing team rather than having the luxury of constructing a whole new team. In both cases, the attribute alignment framework helps identify potential consequences when changing a team's composition such that certain groupings of attributes align (i.e., as in our demonstration of neuroticism-agreeableness alignment predicting relationship conflict).

Finally, it is important to note that the time is ripe for researchers to consider an alignment approach because of the wealth of team composition knowledge that has already been developed using other approaches. The variable-centered approach has yielded a large and useful database of findings explaining particular attributes and their nomological networks. The person-centered approach is less well-established in team research, but insights from the faultlines literature provide knowledge on how multiple attributes predict team subgrouping, primarily based on demographic characteristics. However, because the coexistence of a broad array of attributes has rarely been considered in teams, an alignment approach offers a significant opportunity to leverage this extant theory to explore within and between-person patterns of well-known attributes to advance team composition research.

Future Research Directions

Broader Theoretical Applications. Beyond team composition questions, researchers could also use an attribute alignment approach to address several broader theoretical issues summarized in Table 6. First, this method could be used to compare two non-compositional attributes such as those capturing team member affect, behavior, or cognition. For example, team scholars could explore the tension between group members bringing unique thoughts, feelings, and behaviors to the team context, versus the tendency for teams to develop shared characteristics as they interact (Cronin, et al., 2011; Waller et al., 2016). Group affect research illustrates this point in having identified a set of factors that cause divergence in team members' affective states, despite continuous convergence processes (see Emich & Lu, 2020; Figure 3, for a summary; see also: Emich, 2020; Emich & Vincent, 2020), as does research in social cognitive theory showing that collective efficacy can vary among members of the same team (Gully et al., 2002; DeRue et al., 2010). Researchers could use the attribute alignment approach, for example, to develop hypotheses about how team member affect (e.g., anger) and cognition (e.g., collective efficacy) align to influence shared team processes and outcomes.

Second, the attribute alignment approach could be used to better understand the relationship between two forms of the same attribute, such as (a) the alignment of subjective assessments of an attribute from two sources, (b) the alignment between a subjective and an objective rating of an attribute, and (c) the alignment of values of a given attribute at two different points in time. For instance, the attribute alignment approach could be used to explore the alignment between subjective evaluations from two distinct sources, such as leaders and team members. Research on leader–member exchange (LMX: Janssen & van Yperen, 2004; Wayne et al., 1997), for example, shows that dyadic relationship quality between employees and their supervisors is consequential for individual and organizational functioning. Yet, this literature mainly focuses on member versions of LMX (e.g., Janssen & van Yperen, 2004; Wayne et al., 1997; Zhang et al., 2012, but for an exception see Chaudhry et al., 2021), and implicitly assumes that leaders and members have high agreement on their dyadic relationship quality. An attribute alignment approach allows researchers to explore the similarity or discrepancy between leader and member perceptions of relationship quality.

Further, the alignment approach allows researchers to compare perceived and objective evaluations of a given attribute. For example, teams may be described based on surface-level or objective diversity (e.g., demographic characteristics such as functional background: Harrison et al., 1998) as well as perceived or deep-level diversity (e.g., perceived self-to-team diversity, subgroup split, and group heterogeneity: Shemla et al., 2016). The attribute alignment approach could help link individuals' perceptions and corresponding objective values through examining questions such as do people's perceptions of their team's diversity correspond with objective diversity measures? Or, do people's self-perceptions of expertise match their organization's classification of their expertise? And, what are the drivers and consequences of such matching and mismatching?

Finally, the attribute alignment approach could focus on team emergent states such as attitudes, emotions, and behavioral patterns that represent their inherent dynamism (Marks et al., 2001; McGrath et al., 2000). Emergent states have been theorized for decades, yet we rarely study them as dynamic processes because of the difficulty of data collection and a lack of appropriate longitudinal analysis techniques (Cronin et al., 2011). Building on the work of Lang et al. (2019), we suggest that organizing teams into matrices provides a novel and rather simple solution to measuring changes in attributes, including emergent attitudes, emotions, and behavioral patterns, by defining the matrix in terms of team members by time. In this way, our framework allows consideration—at the team level—of how much individual members' attributes change between two (or more) points in time.

Considering the Alignment of More Than Two Attributes. Another extension of the attribute alignment approach presented here is the potential to accommodate more than two attributes. Because this approach

Table 6. Additional Theoretical Applications of the Attribute Alignment Approach.

Alignment type	Explanation	Example of vector 1	Example of vector 2
Alignment between two attributes	The alignment between two within-person attributes (descriptive, affective, behavioral, or cognitive), across the team.	Team members' attribute A (e.g., anger)	Team members' attribute B (e.g., collective efficacy)
Alignment between two forms of one attribute	The alignment between two perceptions of an attribute.	Perception of source 1 (e.g., team members' perceived leader–member exchange quality)	Perception of source 2 (e.g., leader's perceived leader–member exchange quality)
	The alignment between a perceived attribute and the objective value of that attribute, across the team.	The objective value of team members' attribute (e.g., each member's amount of information exchanged)	Team members' perception of this objective value (e.g., each member's *perceived* amount of information exchanged)
	The alignment between a single team member attribute at two time points, across the team.	Attribute at time 1 (e.g., team members' collective efficacy)	Attribute at time 2 (e.g., team members' collective efficacy)

considers teams as matrices, it is capable of modeling the alignment of any number of attributes relevant to a given theory or research question. For example, Hambrick et al. (2015) proposed that multiple attributes of individual members of a board of directors might predict effective monitoring. They argue that the four critical attributes of a director include: (1) independence, (2) expertise in the domain, (3) bandwidth to devote time and attention to board activities, and (4) motivation to expend effort on behalf of shareholders. Critically, they also claim that these four attributes are best situated within at least one individual director —a "quad-qualified director"—rather than having high scorers on each of these four attributes distributed across different directors. Other examples include simultaneously examining the alignment of multiple personality attributes (e.g., the six dimensions of the HEXACO: Veselka et al., 2009) or examining a focal attribute in the context of a given personality configuration (e.g., asking whether it matters if neuroticism and agreeableness *and* leadership status align).

The approach outlined in this paper provides the conceptual and empirical base for investigating such questions. Future work could build on this initial conceptualization by adding an extra column or columns to a given team's attribute matrix to account for these additional attributes of interest. Then, one could compare the closeness of the resulting vectors. As a first step in this exploration, we suggest researchers interpret team member attribute vectors as point masses instead of defining alignment through a physical interpretation (Fasshauer & McCourt, 2015). A physical interpretation such as the area or perimeter of a set of vectors may break the assumption of symmetry between attributes, particularly when no unique convex polygon exists to differentiate particular sets of attribute vectors. However, considering attributes as point masses allows researchers to calculate the gravitational potential energy of the resulting system or their electrostatic potential (see Halliday et al., 2013). In this way, attributes that are closer together produce higher values and thus indicate more alignment without the potential disadvantages of using the area or perimeter of the attribute system. Overall, considering a geometric interpretation of team members and their attributes allows scholars the freedom to adapt measures to empirically test a wide variety of research questions.

Conclusion

We believe that the insights gained from the attribute alignment approach presented here will aid scholars in better matching team composition theory with its empirical study by providing them the opportunity to ask and answer new and important questions, such as: "Does it matter who on a team has which attributes?" Being able to answer these types of questions matters both theoretically and practically as both scholars and managers ask such questions that neither the variable-centered nor the person-centered approach can fully address. Thus, the attribute alignment approach is a useful tool for operationalizing and advancing team composition research.

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Notes

1. For this particular example, it is the case that all the entries are integers, but there is no guarantee that the metrics researchers employ will yield integer similarities, for example if one is measuring an attribute using the mean of a scale with multiple items. Thus, we simply state that values must be real numbers, i.e., in R.
2. Another key assumption is the stationarity of the scale on which a given attribute lies, e.g., the difference between 1 and 2 must be equivalent to difference between 2 and 3, etc. The data can be continuous (not necessarily integer-valued), but the data should be rescaled in order to have this desired stationarity. This is normally accounted for in the scale building process; however, for the alignment value to be as meaningful as possible, and for its interpretation to be useful, researchers should ensure that differences between all points on a given scale are equal. In machine learning, such rescaling is sometimes done with the Beta or Kumaraswamy distributions (Snoek et al., 2014), which would be equally appropriate in this setting.

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Appendix A

In this appendix, we more clearly describe the benefits of using the p-norm to operationalize the alignment of two attributes within members across the team. One significant benefit of our team feature construct is that we only consider relationships which satisfy the symmetry and permutation invariance properties. Although searching a more general model space provides more opportunities for possible model fit, it also leads to a weaker statistical analysis. Rewriting the $||x-z||_2$ quantity as a linear model of the individual attributes would require a full Taylor series because of the square root present. We can instead demonstrate the benefit of our proposed feature on the $||x-z||_2^2$ quantity, which can be expressed with only second-order interactions between individual-level attributes. The linear series containing all second-order terms between two attributes of a team with d team members is as follows:

$$a+\sum_{i=1}^{d} b_i x_i + c_i z_i + d_i x_i z_i + e_i x_i^2 + f_i z_i^2 + \sum_{i,j=1, i\neq j}^{d} g_{ij} x_i z_j$$

and the expansion of the $||x-z||_2^2$ quantity is as follows:

$$\|x-z\|_2^2 = \sum_{i=1}^{d} -2x_i z_i + x_i^2 + z_i^2$$

Learning the appropriate coefficients $b_i=0$, $c_i=0$, $d_i=-2$, $e_i=1, f_i=1$, $g_{ij}=0$ from the data to reproduce the structure in the distance feature would require a great deal of data, far more than is likely to be available in most practical circumstances. Moreover, to actually include the square root would require infinitely many terms in the series expansion.

We argue that, since no specific model structure is supported from first principles by the test circumstances, we should seek to find the model which satisfies our desired properties in the simplest fashion possible. As a demonstration, consider the situation where teams with $d = 3$ members are undergoing team-level analysis using this 2-norm feature (squared to simplify the comparison)

$$p_i = \alpha + \beta[(x_{i1} - z_{i1})^2 + (x_{i2} - z_{i2})^2 + (x_{i3} - z_{i3})^2]$$

in contrast to the linear model including all second-order terms

$$\begin{aligned} q_i =& a + b_1x_{i1} + b_2x_{i2} + b_3x_{i3} + c_1z_{i1} + c_2z_{i2} + c_3z_{i3} \\ &+ d_1x_{i1}z_{i1} + d_2x_{i2}z_{i2} + d_3x_{i3}z_{i3} + e_1x_{i1}^2 + e_2x_{i2}^2 + e_3x_{i3}^2 \\ &+ f_1z_{i1}^2 + f_2z_{i2}^2 + f_3z_{i3}^2 + g_{12}x_{i1}z_{i2} + g_{13}x_{i1}z_{i3} + g_{21}x_{i2}z_{i1} \\ &+ g_{23}x_{i2}z_{i3} + g_{31}x_{i3}z_{i1} + g_{32}x_{i3}z_{i2}. \end{aligned}$$

With our team alignment feature, we can run a single hypothesis test $H_0{:}\beta = 0,\ H_1{:}\beta \neq 0$ to determine whether the attributes influence the alignment through the 2-norm distance. That hypothesis test only tests for this specific influence, but in targeting that specific influence the power of the statistical analysis is high (low chance of missing a significant outcome). In contrast, to reach that same conclusion with the more general model, we would need to conduct 21 hypothesis tests; assuming that each were conducted with the same probability of Type I error as the single alignment hypothesis test, the statistical power of the complete analysis would be significantly lower.

This idea of building the right feature for our team level analysis can be viewed as similar to the development of machine learning strategies. Neural networks learn all of the weights in their models from what is often just the raw data (e.g., an image); this gives them the ability to model a very broad set of problems, and learn subtle and unexpected patterns, but demands a massive amount of data to be able to successfully perform. Additionally, Kernel methods in approximation theory (Fasshauer & McCourt, 2015) and machine learning (Schölkopf & Smola, 2018) provide numerous examples of distance being a building block for modeling information. Radial basis functions (RBFs) are the natural extension of that, allowing distance to interact with the metric to be modeled in a precise and tunable fashion. But the simplest RBF is still the Euclidean distance, which continues to be a popular tool for many computational purposes (Flyer et al., 2016). Indeed, the distance serves our purposes well, but future work will likely involve the increased flexibility of general kernel methods in the team member attribute aggregation process.

Appendix B

The code provided below is for generating team attribute alignment values in Python 3.5. No external libraries are imported here; a more efficient version of this could be written using a computational library such as NumPy. We provide four sets of code. The first two sets of code show (1) how to compute team attribute alignment using a 2-norm for a single team, and (2) how to compute team attribute alignment using a 2-norm for a set of teams such as the set of 92 teams in our study. The second two sets of code show (3) how to compute the vector angle between two attributes for a single team, and (4) how to compute the vector angle between two attributes for a set of teams. In all cases, no missing values are assumed, as was the case in our study.

Function for Computing the 2-Norm Alignment Within a Single Team

In this situation, we assume that the two attributes (from the same team) have been consistently ordered in lists. This assumption guarantees that the attributes from all the team members have been included (though maintaining a consistent order is incumbent on the user).

```
def alignment_two_attributes_2norm(attribute_1, attribute_2):
    d = len(attribute_1)
    assert len(attribute_2) == d
    alignment_squared = sum((a_1 - a_2) ** 2 for a_1, a_2 in zip(attribute_1, attribute_2))
    return (alignment_squared / d) ** .5
```

Function for Computing the 2-Norm Alignment for a List of Multiple Teams

In this situation, we assume that the team data is organized as a list of dictionaries. These might look like the following:

```
def alignment_two_attributes_2norm_list(data, attribute_name_1, attribute_name_2):
        alignment_list = []
        for team in data:
                team_id = team['team_id']
                attribute_1 = data[attribute_name_1]
                attribute_2 = data[attribute_name_2]
                alignment = alignment_two_attributes_2norm(attribute_1, attribute_2)
                alignment_list.append({'team_id': team_id, 'alignment': alignment})
    return alignment_list
```

It could also be possible to index the data by an individual (which would look more like a spreadsheet). This function returns a list of dictionaries containing the team id and alignment value. It assumes that the earlier function, alignment_two_attributes_2norm, has already been created.

```
def alignment_two_attributes_angle(attribute_1, attribute_2):
    d = len(attribute_1)
    assert len(attribute_2) == d
        inner_product = numpy.dot(attribute_1, attribute_2)
        norm_attribute_1 = numpy.dot(attribute_1, attribute_1) ** .5
        norm_attribute_2 = numpy.dot(attribute_2, attribute_2) ** .5
    return numpy.arccos(inner_product / (norm_attribute_1 * norm_attribute_2))
```

Function for Computing the Angle Alignment for a Single Team

The angle computation requires the external library NumPy to be imported for computation of the inverse cosine.

```
def alignment_two_attributes_angle_list(data, attribute_name_1, attribute_name_2):
        alignment_list = []
        for team in data:
                team_id = team['team_id']
                attribute_1 = data[attribute_name_1]
                attribute_2 = data[attribute_name_2]
                alignment = alignment_two_attributes_angle(attribute_1, attribute_2)
                alignment_list.append({'team_id': team_id, 'alignment': alignment})
    return alignment_list
```

Function for Computing the Angle Alignment for a List of Teams

```
alignment_two_attributes_2norm <- function(attribute_1, attribute_2) {
    d <- length(attribute_1)
    stopifnot(length(attribute_2) == d)
    alignment_squared <- sum((attribute_1 - attribute_2) ** 2)
    return(sqrt(alignment_squared / d))
}
```

Appendix C

The code provided below is for generating team attribute alignment values in R, version 4.0.5, in terms of both vector norm and vector angle. As with the Python 3.5 code, it assumes no missing values.

Function for Computing the 2-Norm Alignment for a Single Team

```
alignment_two_attributes_2norm_matrix <- function(attribute_1_matrix,
attribute_2_matrix) {
    stopifnot(all(dim(attribute_1_matrix) == dim(attribute_2_matrix)))
    return(sqrt(rowSums((attribute_1_matrix - attribute_2_matrix) ** 2)))
}
```

Function for Computing the 2-Norm Alignment for Two Full Matrices of Multiple Teams

Note: In R we use "two full matrices of multiple teams" as R more naturally prefers matrix objects.

```
alignment_two_attributes_angle <- function(attribute_1, attribute_2) {
    d <- length(attribute_1)
    stopifnot(length(attribute_2) == d)
    inner_product <- (attribute_1 %*% attribute_2)[1]
    norm_attribute_1 <- sqrt((attribute_1 %*% attribute_1)[1])
    norm_attribute_2 <- sqrt((attribute_2 %*% attribute_2)[1])
    return(acos(inner_product / (norm_attribute_1 * norm_attribute_2)))
}
```

Function for Computing the Angle Alignment for a Single Team

```
alignment_two_attributes_angle_matrix <- function(attribute_1_matrix,
attribute_2_matrix) {
    stopifnot(all(dim(attribute_1_matrix) == dim(attribute_2_matrix)))
    a <- attribute_1_matrix
    b <- attribute_2_matrix
    return(acos(rowSums(a * b) / sqrt(rowSums(a * a) * rowSums(b * b))))
}
```

Function for Computing the Angle Alignment for Two Full Matrices of Multiple Teams

Note: In R we use "two full matrices of multiple teams" as R more naturally prefers matrix objects.