Team Composition Revisited:

Expanding the Team Member Attribute Alignment Approach to Consider Patterns of More than Two Attributes

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Abstract

The attribute alignment approach to team composition allows researchers to assess variation in team member attributes that occurs simultaneously *within* and *across* individual team members. This approach facilitates the development of theory testing the proposition that individual members are themselves complex systems comprised of multiple attributes, and that the configuration of those attributes affects team-level processes and outcomes. Here, we expand this approach, originally developed for two attributes, by describing three ways researchers may capture the alignment of three or more team member attributes: 1) a geometric approach, 2) a physical approach accentuating ideal alignment, and 3) an algebraic approach accentuating the direction (as opposed to magnitude) of alignment. We also provide examples of the research questions each could answer and compare the methods empirically using a synthetic dataset assessing 100 teams of 3-7 members across four attributes. Then, we provide a practical guide to selecting an appropriate method when considering team-member attribute patterns by answering several common questions regarding applying attribute alignment. Finally, we provide code (https://github.com/kjem514/Attribute-Alignment-Code) and apply this approach to a field data set in our appendices.

Keywords: team composition, attribute alignment, team roles, team personality

The attribute alignment approach to team composition is a new way of recognizing the complexity of individual team members in the context of their teams (Emich et al., 2022). This approach allows researchers to consider variation *within* and *across* individual team members both conceptually and methodologically. This is distinct from traditional approaches to team composition that model one attribute at a time across a given set of members (i.e., a variable centered approach), or model the co-occurrence of attributes within members to consider subgrouping (i.e., a person centered approach) (Howard & Hoffman, 2018). The strength of this approach is that it considers teams as complex systems composed of members who themselves contain multiple attributes and belong to an overarching collective (Arrow et al., 2000; Kozlowski & Klein, 2000).

Emich et al. (2022) explain attribute *alignment* conceptually as the coexistence of team member attributes within individual team members and across the team (e.g., team members who are optimistic are also assertive and team members who are not optimistic are not assertive). In contrast, *unalignment* reflects dissimilar levels of attributes within team members across the team (e.g., team members who are optimistic are not assertive and team members who are not optimistic are assertive). *Misalignment* reflects the lack of a discernable pattern of attributes within members across the team. To capture attribute alignment methodologically, Emich et al. (2022) advocate a geometric approach mapping team member attribute vectors in a multidimensional space. Then, they use the distance or angle between these attribute vectors as measure of the alignment between attributes of interest. The resulting alignment score exists at the team level, and can therefore be used in statistical models estimating team-level processes and outcomes.

However, the examples and procedures outlined in Emich et al. (2022) are limited to alignments involving two attributes, which is problematic for researchers interested in the alignment of three or more attributes. Indeed, many team composition and team process theories increasingly involve the coexistence of more than two attributes. For example, alignment of the four transformational leadership behaviors (i.e., idealized influence, inspirational motivation, intellectual stimulation, and individual consideration) will likely improve the distinction between who is considered a transformational leader in a team and who is not (Bass & Riggio, 2005). Similarly, work on team roles identifies six distinct roles that team members may have unique propensities to adopt, and asks whether it is better to differentiate roles across members or to concentrate multiple roles within one or more members (Mathieu et al., 2015). Finally, the question of how the Big Five factors of personality combine in teams has been a perennial topic of interest in the organizational sciences (e.g., Barrick et al., 1998; Bell, 2007; Colbert et al., 2014; Mohammed & Angell, 2003; Moynihan & Peterson, 2001; Neuman et al., 1999).

To address such questions, we extend the attribute alignment framework to consider the alignment of more than two attributes. We begin by explaining the conceptual similarities and differences between two-attribute alignment and the alignment of three or more attributes. We then propose three different methodologies for operationalizing the alignment of three or more attributes, with examples and research questions illustrating when each would be most useful. Then, we provide simulated data to show how these methodologies are similar and different when calculating four attribute alignments in 100 teams of three to seven members. We conclude by providing answers to expected questions about the attribute alignment approach, along with a step-by-step guide for using this approach in scholarly research.

Considering the Alignment of Three or More Attributes

Conceptualizing and operationalizing alignment is straightforward when considering the alignment of two attributes because two-attribute alignment involves only one pairwise alignment (i.e., comparing Attribute A to Attribute B, which is the same as comparing Attribute B to Attribute A). However, conceptualizing and operationalizing alignment becomes much more complex when considering more than two attributes. The alignment of three or more attributes involves multiple pairwise alignments, the number of which grows drastically as the total number of attributes under consideration increases. For example, three attributes conceptually align in a team when there are team members who score higher on all three and team members who score lower on all three. Unalignment, however, can take on different configurations in this case because there are now three pairwise alignments between attributes (Attribute A to B, A to C, and B to C), any one of which can contribute to unalignment. Empirically, there are ways to tell which pairwise alignment accounts for a given effect, which we describe later. However, because we must consider multiple pairwise comparisons that can manifest differently, there is no single metric that best describes all potential attribute systems involving three or more attributes.

As such, we propose three methods to calculate the alignment of more than two attributes, each of which may be useful in different situations. The first *geometric approach*
directly builds on Emich et al.'s (2022) use of mean square distance to calculate attribute alignment. This method emphasizes equal weighting of distances between attributes (i.e., the average level of alignment between all attributes in the system defines the global alignment of that system). It is ideal for testing general research questions pertaining to alignment, such as: Does the pattern of alignment and unalignment among team member attributes matter? For

example, are teams more innovative to the extent that team member openness, intelligence, and extraversion align (where team members who are higher on openness are also higher on intelligence and extraversion, and team members who are lower on openness are also lower on intelligence and extraversion)? Questions like these assume isomorphism in the system and thus additivity between pairs of attributes (e.g., the alignment of openness, intelligence, and extraversion is exactly equal to the effect of their aggregate pairwise alignments). This approach is therefore the most generally applicable when researchers have no *a priori* expectations that specific pairwise configurations of three or more attributes must or must not align to produce expected effects.

The second *physical approach* uses potential energy to capture the general closeness of attributes. This approach allows a single large pairwise alignment to account for a large amount of global alignment, and this sense of alignment increases drastically as more attributes align. So, a team with all four of a given set of attributes aligned is considered much more aligned than a team with three of those attributes aligned, which is considered much more aligned than a team with only two aligned attributes. It is ideal for addressing research questions with specific assumptions about the necessity of the set of attributes, such as: Does it matter if *all* team member attributes align, as opposed to some of them? Using the example above, a researcher may assume that teams in which openness, intelligence, and assertiveness align perform *much better* than teams in which only two of these attributes align, and much better than if these alignments were considered additively. For example, the researcher may predict that if any one of these attributes does not align with both of the others (e.g., those with the most intelligence are also the most open to new ideas but are the least assertive, or those who are the most assertive are also intelligent but are the least open to new ideas, etc.) then team innovation greatly suffers.

Therefore, alignment between all three attributes is assumed to be crucial, as any amount of unalignment reduces innovation significantly. Therefore, this metric is appropriate when researchers suspect that all of a given set of attributes must align to produce an expected effect.

Finally, the third *algebraic approach* emphasizes the direction of, or interdependence between attributes, instead of distance or closeness (e.g., the system is aligned if attributes point in the same direction across members). This is similar to Emich et al.'s (2022) use of vector angle for calculating two-attribute alignment, indicating the direction of the attributes that comprise the system, as opposed to their magnitude. It is appropriate for answering research questions such as: Does the relative level of team member attributes matter? The example of openness, intelligence, and extraversion may not be appropriate to this question, as a researcher would likely suspect that objective levels of these attributes (versus relative levels) would matter for team innovation. Here, questions for which relative levels versus absolute levels are important are more ideal. For example, team role differentiation may occur more quickly when members' expertise is more specialized relative to their teammates, regardless of their overall levels of expertise (e.g., the best presenter among teammates will be the team's designated presenter regardless of their objective ability). This metric is appropriate when relative relationships among attributes are more important than the magnitudes of those attributes.

-----Insert Table 1 about here-----

We summarize the strengths and weaknesses of these three methodologies in Table 1. Next, we examine each of these three methods in more detail, providing an example research question to guide the use of each method, followed by a detailed explanation of what the method entails. We also provide the mathematical derivations of our alignment operationalizations in Appendices A-C, an empirical step-by-step example of how to consider the alignment of three

attributes using MBA field data in Appendix D, and code in Python and R for calculating all three alignment types online at https://github.com/kjem514/Attribute-Alignment-Code and in Appendix E.

Approach 1: The Geometric Approach

The geometric approach, which builds directly on the two-attribute alignment calculation in Emich et al. (2022), allows each pairwise alignment of a given set of attributes to be represented equally in the system's global alignment, with larger distances indicating less alignment between attributes (see Table 1). This is the most straightforward approach to modeling the alignment of more than two attributes, particularly if there are no a priori reasons to suspect that any given pairwise alignments should contribute unequally to the global alignment score. Therefore, the geometric approach is broadly applicable for investigating the effects of attributes that have traditionally been given similar weighting in a broader system or typology. Examples include the four dimensions of transformational leadership (Bass & Riggio, 2005), the six team roles (Mathieu et al., 2015), or personality frameworks such as the Big Five (Digman, 1990) or the Dark Triad (Paulhus & Williams, 2002).

Using the Dark Triad as an illustration, a researcher could investigate whether alignment of the three attributes in the Dark Triad (i.e., Machiavellianism, Narcissism, and Psychopathy) within and across team members affects team functioning. Alignment would conceptually mean that there are team members who score higher on all three attributes and team members who score lower on all three attributes, with others in the middle. The researcher might predict that such alignment results in empathic differences across team members (i.e., some team members have lower empathy for others and are manipulative, whereas others have higher empathy and concern for others), resulting in low team cohesion. In this case, there may be no reason that an

alignment metric should 'weight' any particular pairwise alignment more strongly than any other or expect that alignment of all three are necessary to produce effects on cohesion. If two of these attributes align it will likely reduce cohesion a bit and if all three align it will likely reduce cohesion a bit more.

To address these types of questions, we suggest taking a geometric approach to calculating attribute alignment building on Emich et al. (2022). The current geometric approach relies on considering the distance between vectors representing team members (*i*) and their attributes (*j*) (Emich et al., 2022). In this sense, each vector (set of a given attribute across team members) can be interpreted as a point in a *d*-dimensional space where *d* is the number of members on a given team. For *a* points there are $\frac{1}{2}a(a-1) \equiv v$ pairwise alignments between attributes. For example, comparing three attributes results in three pairwise alignments, comparing four attributes results in six pairwise alignments, and comparing five attributes results in ten pairwise alignments[1].

Researchers can simply adapt the consideration of attribute alignment in Emich et al. (2022) to more than two attribute vectors by taking the mean square distance between attribute vectors. This can be defined as: $\frac{1}{v}(\delta_1 + ... + \delta_v)$ or $\frac{1}{v}\sqrt{(\delta_1 + ... + \delta_v)}$. We detail why taking this approach is preferable to other geometric approaches, particularly those which may consider a vector system as a polytope with volume and surface area, in Appendix A. In sum, we view the geometric approach as the default method for calculating alignment between more than two attributes, although other metrics may serve different purposes.

Approach 2: The Physical Approach

[1] We denote this as $\delta_1, ..., \delta_v$.

As opposed to the geometric approach, which averages the distance between each pair of attributes to define alignment, a physics-based interpretation allows researchers to consider the closeness of multiple attribute vectors as they would exist in a physical space. This approach elevates the importance of each pairwise alignment in contributing to a global alignment score. In it, the system as a whole is considered more aligned if any part of it is aligned (i.e., any one pairwise alignment is high), and this consideration increases quadratically as more and more attributes align (i.e., as multiple pairwise alignments are high). This metric may therefore be relevant when researchers expect that every pairwise alignment is necessary for the attribute system to be considered aligned, as opposed to the notion that some pairwise alignments in a system are sufficient for the system to be considered aligned.

For example, meta-analysis indicates that four of the Big Five personality traits (i.e., extraversion, openness, emotional stability, and conscientiousness) are related to leader emergence in teams (Judge et al., 2002). As such, a researcher may theorize that the alignment of all four attributes results in clear leader-follower roles in the team (some team members are extraverted and open and emotionally stable and conscientious, while others are not all four of those things). Moreover, the researcher could theorize that leader emergence will be the clearest when all four attributes align, significantly less clear when only three align (e.g., those who are open, emotionally stable, and conscientious are the least extraverted; or those who are extraverted, open, and emotionally stable are the least conscientiousness), significantly less clear again when only two align (e.g., those who are open and emotionally stable are low in conscientiousness and extraversion), and significantly less clear again when none align.

Importantly, the core aspect of this theory is that the primary outcome associated with the attribute system under consideration, leader emergence, is significantly hampered to the degree

that more attributes within the system are unaligned. Thus, the researcher's theoretical model assumes that the alignment of all four attributes is crucial for individuals to emerge as clear leaders and this is what dictates the use of the physics approach for calculating alignment. If the researcher does not have a priori expectations regarding the importance of each pairwise alignment in producing the expected effects (e.g., they suspect that clear leader emergence depends on the degree to which these attributes exist within individuals across the team, even if all four attributes do not closely align), the geometric approach would suffice.

Although it is possible to interpret the relationship of physical phenomena in multiple ways, here we consider the attribute vectors as point charges and define alignment using the electrostatic potential energy of such a system (Griffiths, 2017)[2]. This general quantity – the potential energy of the system of team attributes – denotes the global alignment between a attributes. We define this quantity, modified to satisfy practical considerations concerning team composition (e.g., team size), in Appendix B.

Following the superposition principle, the total potential energy of a system of point charges increases as each pair of point charges gets closer (Griffiths, 2017). Consequently, as team member attributes become closer in this physical space, the potential energy of the system increases, indicating greater global alignment. More precisely, pairwise alignment scores affect the global alignment score in two ways. First, as two attribute vectors become closer, and single pairwise alignment values increase, global alignment will also increase. Second, as multiple pairwise alignments increase, global alignment greatly increases (see Figure 1, below). So, if Attribute A and Attribute B *or* Attribute A and Attribute C *or* Attribute B and Attribute C align more within a given team, that team's global attribute alignment increases. However, if all three

[2] It is also possible to consider other physical measures such as the gravitational force between vectors.

attributes align such that Attribute A and Attribute B *and* Attribute A and Attribute C *and* Attribute B and Attribute C align within a given team, that team's global alignment score increases quadratically. In short, if there is some amount of pairwise alignment, there will be some amount of global alignment. However, this cannot be maximized unless all attributes are in alignment. Alternatively, the only way global alignment is low or absent is if multiple pairwise attributes are out of alignment. Note that this strategy still relies on gaining a sense of pairwise distance to capture the pairwise alignment of attribute vectors. However, it considers this distance in the context of the potential energy of the system.

Overall, the primary advantage of using a physics-based approach is that global alignment values become drastically higher as a greater number of pairwise attributes align, which highlights the effects of 'perfect' alignment better than the geometric approach.

Approach 3: The Algebraic Approach

The algebraic approach allows researchers to account for a sense of how similarity in the direction of attributes contributes to global alignment, instead of similarity in their magnitudes. This calculation takes into account the linear independence of the attribute vectors and will detect high alignment even if all the pairwise alignment vectors are different in terms of distance, as long as they "point" in the same direction. We recommend this method when vectors have different variances, which cannot be equalized through transformation, such as if vectors exist on nonfinite scales where transformation may alter the meaning of the measure. For example, a similar approach is used in the strategy literature to account for differences in patent portfolios between large and small firms (e.g., Kay et al., 2014). Conceptually, this method is useful when a researcher is less interested in magnitudes of pairwise alignments and more interested in relationships between their patterns.

One potential example of the use of this approach is a scholar who is interested in the alignment of three team roles within and across team members: organizer, team builder, and connector (Mathieu et al., 2015). When these three align, there are team members with the tendency to adopt all three roles (organizing and team building and connecting) and others who are not oriented towards them. Alternatively, unalignment indicates that each team member tends to be relatively higher on their orientation toward a single role. In this case, if the researcher was interested in whether there is role clarity or differentiation, the direction of the attribute vectors may be more relevant than the distances between them. For instance, it may not be necessary that the team member who is oriented towards organizing is an extreme organizer, but rather that he is more of an organizer than others on the team (and thus more likely to engage in those behaviors because of the context of that specific team), while other members are relatively higher in their tendency to team build or to connect the team to outside resources. Again, we believe that the geometric approach is likely the most straightforward to calculating attribute alignment in typologies or frameworks such as the Team Role Experience and Orientation framework (Mathieu et al., 2015). Yet, roles and other such concepts may also lend themselves to relative comparisons versus those of magnitude, and the algebraic approach offers an additional way of calculating alignment in these instances.

To model alignment algebraically, we recommend a method involving the singular value decomposition (SVD). We derive this formulation in Appendix C. Higher values indicate higher similarity in attribute direction, thus higher alignment. When exploring the distances between vectors is not desirable, Emich et al., (2022) advocate using a vector angle. However, one cannot calculate an angle between three or more points. The SVD provides a mechanism for studying linear independence of more than two attribute vectors. Two vectors are linearly dependent if

they "point" in the same direction, e.g., the vectors (1, 1, 1) and (2, 2, 2) are linearly dependent. As the vectors point in increasingly different directions, they become more linearly independent, until they point in fully orthogonal directions. In essence, the formula presented in Appendix C allows researchers to account for a different sense of similarity among attributes, in terms of direction instead of distance between them.

Summary of Approaches

Each of the three approaches has advantages and disadvantages, which we summarize in Table 1. The table guides researchers to match an appropriate analytic strategy to their theory or research question. First, we recommend the geometric approach as the most generally applicable to attribute alignment questions without specific assumptions about pairwise alignments or reason to believe that the direction of the attributes across team members should matter more than their magnitude. The geometric approach allows each pairwise alignment to be represented equally in the calculation of global alignment. However, there will be times when theory suggests circumstances in which high alignment between any attributes should greatly influence the global alignment of the system. In such cases, researchers should use the physics-based approach. We note that, often, the geometric and physical approaches are likely to yield similar results, since they are based on considering multiple pairwise distances. However, each can uniquely capture distinct patterns in pairwise alignments, which can result in different global alignment scores. Finally, some attributes may not lend themselves to these calculations, and therefore an algebraic approach is likely to be more appropriate for calculating alignment by favoring the direction of the vectors rather than their magnitude.

Empirically Comparing the Three Alignment Approaches

To better clarify how these three approaches to considering attribute alignment relate, we constructed a synthetic dataset and map it in Figure 1. This dataset contains 100 teams of random size between three and seven. Each team has four attributes of interest, which are measured on integer scales from 1 to 5 and randomly assigned to teams. Once these attributes are randomly drawn, we assign them to team members in four distinct patterns represented by the different colors. As such, the four colors indicate four global alignment conditions: blue represents uniformly random, red represents at least one pair of attributes is fully aligned, yellow represents full alignment except at most one attribute pair, and green represents maximum alignment (the random attributes drawn are matched such that all four highest draws are placed in a single team member. This pattern is repeated for the other draws down to the lowest). From blue to red to yellow to green, team global alignment increases.

----Insert Figure 1 about here----

Figure 1 compares these 100 teams' alignment scores using the three alignment approaches described above to highlight how these methods overlap and differ across the four alignment conditions. In Figure 1, the geometric approach is noted as average distance; the physics approach is noted as the potential energy of the system; and the algebraic approach is noted as singular value decomposition (SVD).

First, the upper left panel displays the relationship between average distance and potential energy. As average distance (Y-axis) increases distance increases, which means the system is less aligned. As potential energy (X-axis) increases closeness increases, indicating the system is more aligned. As expected, potential energy is strongly inversely correlated with average distance, which is logical since it is a sum of inverse distances (see Appendix B). In other words, because average distance relies on assessing the *distance* between attribute vectors while the

potential energy calculation relies on assessing their *closeness*, these measures are negatively related. However, there is a key difference in the way the pairwise alignments interact to form global alignment: while values of average distance appear consistently along the y-axis, potential energy values jump along the x-axis based on the condition of team member attributes (from blue to red to yellow and green). This occurs because the potential energy measure is most sensitive to very short distances, thus if any two attribute vectors are extremely close it can become large. And, as the number of pairwise alignments increase, the system creates significantly more energy. In contrast, average distance receives its influence from all pairwise alignments equally. Therefore, the average distance calculation will show stronger alignment as *all* attributes become more aligned – all single pairwise alignments contribute to the global alignment in a linear fashion.

To further illustrate the difference between the average distance method and potential energy approaches, let us take a closer look at the upper left panel of Figure 1. Imagine drawing a horizontal line where Y (i.e., average distance) roughly equals to 1.3. This line crosses the potential energy calculation in all four conditions (blue, red, yellow and green). This means that an attribute system with an average distance of 1.3, may be arranged in any of the four ways described. For example, it could have one short pairwise distance (red) or three of its four attributes could be highly aligned (yellow). However, the potential energy method can detect difference between these two scenarios. Similarly, if you draw a vertical line where X (i.e., potential energy) roughly equals to 0.3, it crosses blue and red Y-values between 1.2 and 2.3 This means that when the potential energy of two systems are similarly small (i.e., as attributes are becoming less aligned and the vectors in the systems are getting further apart), the average

distance measure can still capture their differences using the average of all pairwise distances (since potential energy severely underweights highly unaligned attributes).

This reveals that the average distance approach reflects all pairwise alignment equally and supports the recommendation that researchers should consider this method if their research question predicts that some alignment of three or more attributes is sufficient to consider the attribute system aligned. On the other hand, the potential energy approach is sensitive to increasing pairwise alignments in the system and thus can better capture the differences in systems as the closeness of attributes increases. For that reason, the potential energy method could be used if the theory predicts that alignment of three or more attributes is necessary for an effect to emerge (i.e., rewarding 'perfect' alignment more than other calculations).

Second, because the SVD is not derived from pairwise distance, it is not inherently related to either average distance or potential energy. However, these calculations (where higher values indicate greater alignment) still may tend to correlate moderately as vectors with the same values necessarily take the same direction. This is why in both bottom panels, SVD and the distance measures (average distance and potential energy) correlate so highly in the maximum alignment condition (green), somewhat in the full alignment except one attribute pair condition (yellow), and less so in the one pair aligned (red) and uniformly random (blue) conditions. However, there also exist a variety of vectors with the same direction that are not of the same magnitude (e.g, [1, 1, 2, 3, 3] and [3, 3, 4, 5, 5]). Such cases would show low to moderate alignment using average distance and low alignment using our physics based approach, but high alignment using SVD. We can use the same approach as above to identify such instances. For example, SVD values of 1.5 cut through all four types of both average distance and potential energy alignment, as well as most of the range of these scales. This indicates that, despite the

tendency for these values to be moderately correlated in many instances, SVD does not necessarily do a good job assessing how many attributes are likely to overlap in a given system. For example, having one attribute's direction differ greatly from the others in an attribute system would cause SVD to decrease, even if attribute magnitudes are similar (e.g., [1, 1, 2, 3, 3] and [2, 2, 2, 2, 2]). Alternatively, average distance would find stronger alignment between these vectors than the ones with similar direction mentioned above ([1, 1, 2, 3, 3] and [3, 3, 4, 5, 5]), as would the potential energy measure. These differences in interpretation of global alignment account for the differences observed in Figure 1.

Overall, this unbiased simulation reveals similarities and differences among the three metrics that could be used to calculate the alignment of more than two attributes. For example, although using a geometric (average distance) or physical (potential energy) definition of alignment will result in similar values across many teams, they also differ in certain scenarios. Below, we address how researchers should consider these differences, as well as several other questions concerning how to best use our attribute alignment approach to team composition.

Answers to Seven Common Questions about Attribute Alignment

1. When should I use attribute alignment?

Researchers should, of course, start by considering the theoretical relationships hypothesized in their models before choosing an analytic strategy. As emphasized in Emich et al. (2022) and here, the attribute alignment approach offers team researchers a tool to ask a different set of research questions relative to traditional approaches for understanding team composition. If team researchers are interested in exploring how the extent to which multiple attributes coexisting in some team members relative to others affects team processes and outcomes, they should use an attribute alignment approach.

However, it is important to note that the attribute alignment approach should be viewed as just one tool in a larger toolkit that includes more established variable and person-centered approaches to team composition (Bell et al., 2018; Emich et al., 2022; Howard & Hoffman, 2018). In many instances, research questions will lend themselves to hypotheses or explorations that do not involve attribute alignment, and for which other methodological tools are more appropriate. For example, researchers might be interested in how the absolute levels of particular attributes influence team outcomes, or how these levels interact. In such cases, they should take a variable-centered additive approach focused on how mean attribute values influence team functioning (Chan, 1998). Researchers might also be interested in how the distribution of a given attribute influences team outcomes, or how particular distributions interact. In such cases, they should use a variable-centered configurational approach (Crawford & LePine, 2013). At still other times, researchers might be interested in how subgrouping influences teams. In these cases, they should choose a person-centered approach (Howard & Hoffman, 2018).

2. Can I combine attribute alignment with more traditional approaches to team composition?

While choosing a single approach may be appropriate to answer certain research questions, the attribute alignment approach can also be combined with more traditional additive or configurational approaches to team composition, or other more complex person-centered approaches. As mentioned earlier, additive, configurational, person-centered approaches, and the attribute alignment approach, all focus on distinct aspects of team composition, which means that researchers can consider all of them to reveal a more complete picture of team composition with respect to attributes of interest. For instance, a researcher might wonder how neuroticism affects team innovation. It is theoretically plausible that a larger amount of neuroticism in teams (e.g.,

mean neuroticism), or diversity in neuroticism (e.g., variance of neuroticism), or the alignment of neuroticism with another trait or traits (e.g., extraversion, openness, or intelligence), influences team innovation. As such, researchers may wish to compare approaches to explore what considerations of team composition best address a particular effect. In doing so, as in Emich et al. (2022), they may regress multiple conceptualizations onto an outcome of interest, or add them into another model. That said, it is not necessary to control for any other team composition model when studying attribute alignment as is the case with means, faultlines, and other conceptualizations of team member attributes.

Another way of combining these approaches is to consider interactions between attribute alignment and other team level properties. For example, a scholar might predict that alignment of cognitive ability and emotional intelligence benefits team performance, but that teams must have some threshhold-level of these attributes for this effect to occur. Teams in which members are all low on cognitive ability and emotional intelligence would technically be aligned on these two attributes, but the absence of these attributes is not likely to benefit team performance. Although such cases are likely uncommon in student and professional samples, this example illustrates the idea that team-level magnitudes or other attribute distribution properties may be important when considering questions of attribute alignment. Moreover, beyond considering threshold effects, an interaction may indicate that as levels of an attribute get higher or lower, an alignment effects become stronger or weaker. Similarly, as variances in particular attributes increase – or other distribution properties do, such as minimum or maximum levels – alignment may become more or less important in explaining team processes and outcomes.

Finally, researchers may also consider alignment alongside person-centered approaches such as team faultline analysis (Meyer & Glenz, 2013) or latent profile analysis (Woo et al.,

2018). The most obvious application may be to explore how the alignment of particular attributes leads to subgrouping or the expression of particular behavioral patterns that constitute a team profile. Overall, we encourage researchers to consider alignment alongside these other approaches, and to consider their integration.

3. Which attribute alignment method should I choose?

We strongly recommend that researchers use the attribute alignment approach that best represents their theory. We suspect that the geometric approach – specified for two attribute alignment in Emich et al. (2022) and for three or more attribute alignment in this paper – will suit most research questions about alignment. However, because there are several ways to calculate the alignment of more than two attributes, we present two alternatives to the geometric approach, which are better suited for specific research questions. For example, if a research question concerns attributes measured on scales that cannot be easily compared or transformed to meet requirements for similar variances, or count variables with no meaningful theoretical range, or where relative relationships among attributes are of primary interest and alignment magnitude is not, we recommend using the SVD method. If strong alignment is of theoretical concern, where it is important that all attributes align (versus situations in which some alignment is sufficient) the potential energy method should be considered. Again, absent the theoretical guidance to use another approach, researchers should use average distance to consider team attribute alignment.

Calculating global attribute alignment in each of the three proposed ways may also help researchers understand aspects of attribute alignment that relate the most strongly to a particular team process or outcome, if related theories are under-developed. The descriptions above should provide guidance for such exploratory work. For example, if only the potential energy of the

attribute system positively relates to a specific team process or outcome, this indicates that alignment between greater numbers of attributes is necessary for effects to occur. Alternatively, both the geometric approach and the physics approach may similarly predict an outcome of interest (see Figure 1), which indicates that the alignment effect is not dependent on sets of extremely aligned teams. Again, in such cases we suggest that researchers generally use the average distance measure, unless theoretical guidance or additional data with broader samples provides evidence that the potential energy measure should be used instead.

4. What if my attributes are correlated with each other? What if they are uncorrelated with each other?

Often, researchers will be interested in the alignment of attributes that have established empirical relationships. For example, as Crossan et al. (2017) note, character strengths "form a complex network of correlated constructs" (p. 1004). Figure 1 lends some insight into how this will influence the likelihood of finding differences between the three methods presented here and which method may be most likely to relate to a given team outcome when attributes are highly correlated. First, as attributes become more positively correlated, they are increasingly likely to align in a team. Since the potential energy measure is more sensitive to closeness in an attribute system, this method may be better able to pick up differences between teams in such cases, although such use should still be guided by theory. When attributes are negatively correlated, the opposite is true: attributes within the system are more likely to be unaligned. Because these distances will not contribute much to the potential energy measure, it will most often be appropriate to use the average distance when attributes are negatively correlated. Finally, as Figure 1 displays, the SVD value is less likely to differ from the distance-based measures when attributes are highly correlated. These instances restrict likely differences in direction that may

occur and make it more likely that variations that do occur relate to differences in alignment magnitude.

5. Do I need to include two-attribute alignments when empirically testing for higher alignments?

An important practical question is whether it is necessary to account for two-attribute alignments when examining effects of higher alignments on team processes or outcomes. For example, a researcher may question whether a particular lower alignment accounts for the observed effect of a global alignment score on a particular outcome. One very important point to keep in mind when taking this into account is that considering how a system of attributes aligns is not the same as considering the effects of independent and contingency variables on dependent variables, as in interaction models with main effects. In such models, it is customary to include main effects prior to, and later in conjunction with, entering an interaction term into the model. In attribute alignment, each pairwise alignment should only be accounted for once in a particular model, to reduce concerns about non-essential multicollinearity.

----Insert Figure 2 about here----

The goal of attribute alignment is to create a model that lets researchers study team-level outcomes by considering the relationship among attributes within team members, across the team. Related theories should always guide researchers to define what attributes might align to produce certain effects. For example, a researcher could be interested in all Big Five personality traits, or in three of the traits (e.g., agreeableness, conscientiousness, and openness), or in two of the traits (e.g., agreeableness and conscientious). Once those attributes are chosen, there is a finite set of pairwise alignments that belong to that attribute system. For example, the four-attribute system (where attributes are named A, B, C, D) indicated in Figure 2 defines a set of six

pairwise alignments (numbered 1-6). In this system, if a researcher wanted to consider how the alignment of attributes A-D related to team performance, she could regress team performance onto the alignment of the system (i.e., A-B-C-D alignment). This would account for each pairwise alignment (1-6) once. If the researcher wanted to explore this differently, she could also regress performance onto each of the six pairwise alignments. This would also account for each pairwise alignment once. She could also regress performance onto a mixed set of combinations of attributes, perhaps one three-attribute alignment (i.e., A-B-C alignment) and three two-attribute alignments (A-D, B-D, C-D). Again, this would account for each pairwise alignment once.

However, any given pairwise alignment cannot be included more than once in an analytical model. If a pairwise alignment is included along with a higher alignment including those two attributes, this will create non-essential multicollinearity in the model since it is assessing the same relationship twice in the same model (or more if a researcher included all 2-attribute and 3-attribute alignments in a 4-attribute system, for example). Thus, the terms in the model would not be independent. However, a researcher could conceive of a host of models to test the alignment of the attribute system, *so long as no pairwise alignment is considered more than once*.

One other point to note is that it would not be helpful to create a theoretical model regarding the relationship between A-B-C-D alignment and a team outcome and then only test how A-B alignment relates to that outcome because such an analysis would ignore most of the theoretical model (i.e., it would only account for one of six possible pairwise alignments that comprise the global attribute system). If the main interest is in A-B alignment, the system should be theoretically defined as only including those two attributes.

Finally, we suggest using the same method to calculate lower and higher alignments (i.e., if average distance best describes the theoretical relationship between pairwise and global alignment in the theoretical system, average distance should be used to calculate every level of alignment within that system). The consistency of testing all alignments using the same approach will keep the assumptions of the model similar among any system of lower and higher alignments, allowing commensurate comparisons.

6. Can I apply this method outside of teams?

We have demonstrated how the attribute alignment approach can be applied to teams. However, it can also be applied to any multilevel system where lower-level components contain multiple attributes that may relate to higher-level outcomes. For example, if one wants to consider how the alignment of team attributes (e.g., funding and member skills and abilities) relates to department or branch effectiveness; or, if one wants to consider how the alignment of department or branch attributes (e.g., number of employees and resources given) influences organizational outcomes, a researcher could apply the alignment methods discussed here. The math described in Appendices A-C and the theory discussed throughout this paper will not change, the only shift will be in the level of its application. We believe our description of attribute alignment here establishes the general conceptual meaning of alignment, thus allowing other researchers to apply it to various research questions including and beyond team composition. We look forward to seeing how others build on this approach in unique ways.

7. This is a lot. Do you have a Step-by-Step Guide for Using an Attribute Alignment Approach?

We present a guide below, as well as an empirical example with MBA field data in Appendix D that can be used to follow this guide. When a research question and related theories suggest

value in examining the alignment of multiple attributes in teams (see Q1 and Q2 for details), researchers can take the following five steps in their empirical investigation.

1. *Use theory to define the attribute system.* Theory should always guide researchers in defining what attributes should be included in a focal attribute system. This definition will help to define the global alignment under examination, as well as the lower alignments that may comprise it.
2. *Choose an attribute alignment analysis method.* In a system of only two attributes, researchers may use Emich et al. (2022) as a guide for how to calculate global attribute alignment. If there are three or more attributes, researchers should consider the three methods we present here (See Q3 for details). Briefly, we also have two technical reminders for our fellow researchers. First, the attributes under consideration should have equal variances or the one with greater variance will account for a greater amount of the attribute alignment score. When needed, transformations can be conducted to satisfy this assumption (Emich et al., 2022). Second, if researchers are using the potential energy method, it requires a minimum distance value. See Appendix B for details. Researchers may also develop their own alignment measures as attribute vectors can be compared in numerous ways (e.g., a travelling salesman or gravitational force solution). However, researchers must explicitly acknowledge the assumptions underlying any method they use.
3. *Consider if the relationship between attribute alignment and other variables in your model might vary as a function of other properties of attributes in the system.* As we detail in Q2, attribute alignment can be used alongside other variable- or person-centered approaches to explore a team composition research question. Theory should help guide

researchers in deciding whether attributes' distribution properties (e.g., means, variances, minimum/maximum values) or subgrouping tendencies matter to a particular process or outcome. If so, create appropriate interaction terms and/or control for these effects in your model.

4. *Empirically test your model.* Each model will of course be unique. Our field example in Appendix D provides several illustrations of ways to test attribute alignment. However, researchers must follow best practices regarding whatever model they test. Attribute alignment results in a team-level variable. As such, an alignment value can be used in any model allowing team-level variables.
5. *Interpret significant and non-significant effects in light of theory.* When a significant attribute alignment effect is identified, the next task is to interpret this effect. A significant effect of global attribute alignment generally means that an effect occurs when some team members score higher on all included attributes while others score lower on all of them, whereas a significant unalignment effect indicates that the effect occurs when these attributes coexist at different relative levels within team members across the team. A non-significant effect indicates that the coexistence of those attributes identified within the attribute system does not influence the outcome of interest. After identifying significant and non-significant effects, researchers can explain them in light of their theoretical model (e.g., with respect to specific team processes or outcomes).

Conclusion

In this paper, we describe three methods to assess variation in three or more team member attributes within and across team members. We also demonstrate the relationships between the three approaches and provide practical guidance in using them. Regardless of the specific method used, researchers need to carefully consider how attributes of interest

theoretically relate to one another and team processes and outcomes before using the attribute alignment methods described here, or any other aggregation technique. We hope, in doing so, that researchers embrace the complexity of individual team members and the teams they make up, so that we can better understand how the systems of attributes that comprise individual members relate to broader collective behavior.

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Table 1. Advantages and disadvantages of different 3+ attribute alignment methods

	Method	Classification	Pairwise Contribution to Global Alignment	Advantages	Disadvantages	When to Use
1	Root Mean Squared Distance	Geometric	Equal	Equally combines pairwise alignments.	Considers alignment as distance.	A researcher wants to consider all pairwise alignments equally.
2	Potential Energy of the System	Physical	Extreme Closeness Contributes More	Considers alignment as closeness. Clearly differentiates alignment systems with different numbers of highly aligned attributes.	Less sensitive to highly unaligned attributes. Needs minimal distance threshold so as not to create infinite energy.	A researcher is interested in systems where greater alignment among more attributes affects an outcome of interest.
3	Singular Value Decomposition	Algebraic	N/A	Can account for direction of alignment, including situations in which attribute vectors have unequal variances or exist on nonfinite scales.	Cannot account for magnitude of alignment.	A researcher is interested in systems where greater alignment is defined as the direction (not magnitude) of different team member attributes.

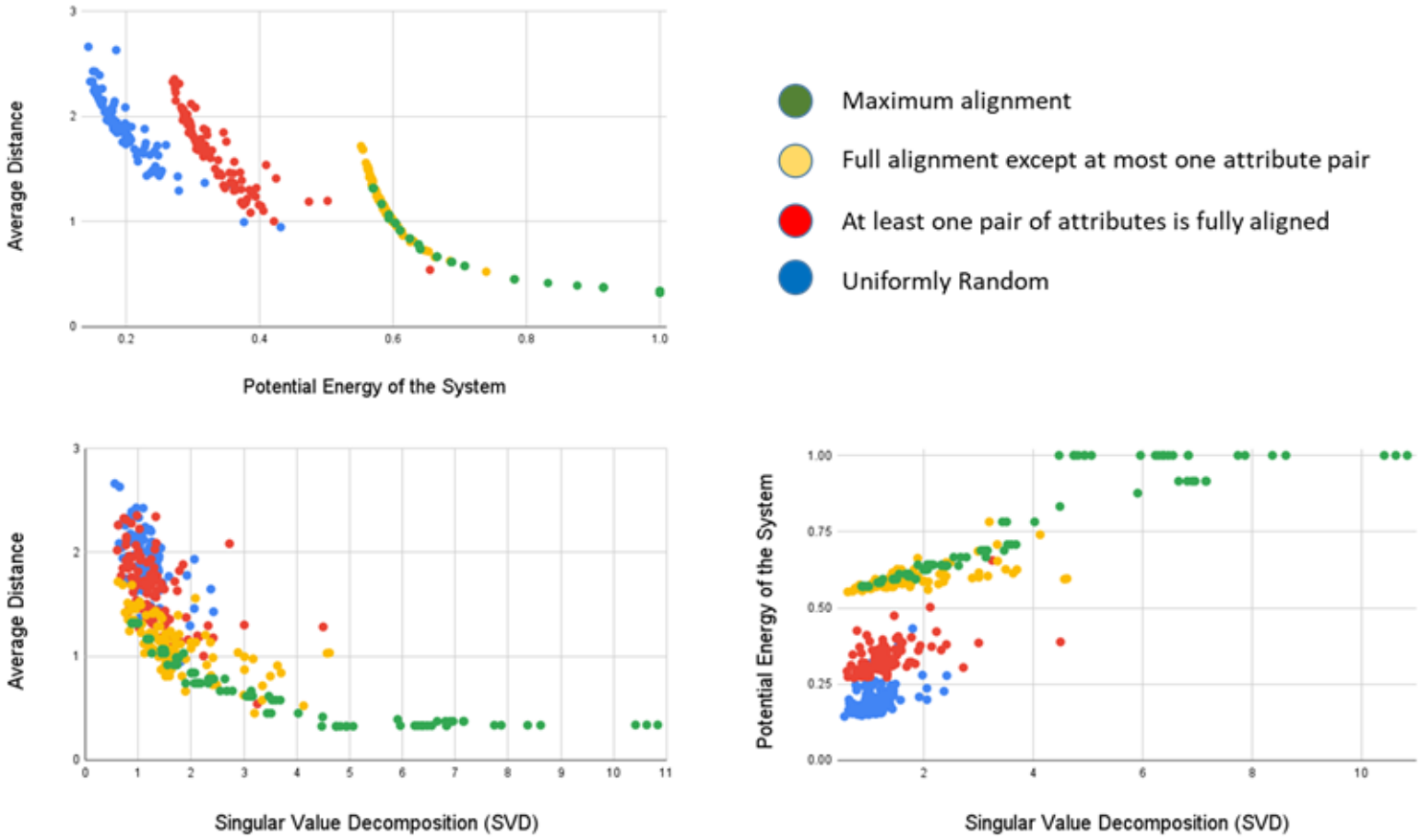

Figure 1. Plotting the relationships between definitions of global alignment.

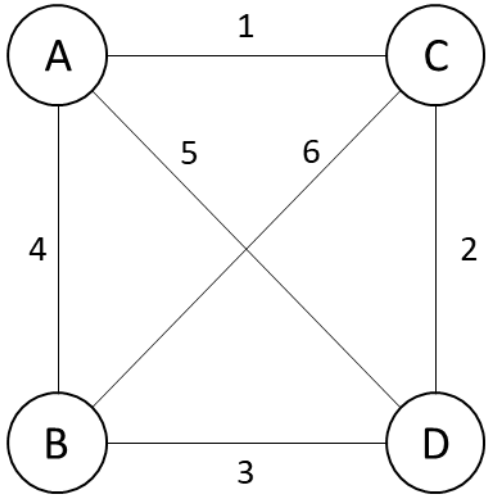

Figure 2. A hypothetical 4-attribute system (labeled A-D) containing six pairwise alignments (labeled 1-6).

Appendix A: Notes on a geometric approach to attribute alignment.

Importantly, many polytopes can result from the set of pairwise alignments that comprise an attribute system. The most logical analogue to distance from a geometric perspective is the volume or surface area of the associated polytope that connects three or more points (i.e., vectors). Indeed, one can create attribute vectors for any number of attributes and compare them using geometric quantities such as volume or surface area such that they retain symmetry and permutation invariance, which Emich et al. (2022) describe as necessary preconditions to compare attribute vectors. The computation of these quantities is much less straightforward than calculating the Euclidean distance between points. Büeler et al. (2000) listed strategies for exactly and approximately computing the volume quantity, but also noted the complexity of any such computations. Similarly, Belkin et al. (2006) explained how the best strategies for surface area computations are limited by volume computations, making surface area no more practical. Beyond this, calculating such geometric properties in a *d*-dimensional space (e.g., plotting a triangle in 5-dimensional space when considering 3 attributes on a 5-member team) suffers a computational limitation when defining alignment – such calculations degenerate under certain orientations of the points. For example, a triangle would collapse into a line if its points were collinear, and the resulting volume and surface area would be ill-defined (or 0, arguably). This prevents scholars from distinguishing between a situation where two of three attributes are the same (some amount of misalignment) and all three attributes are the same (complete alignment). As such, while considering attribute vectors as a polygon in multidimensional space may seem like the most obvious way to geometrically consider an attribute system, we advise against it; and instead advice scholars to use the average distance approach described in this manuscript.

To recap, researchers can simply adapt the consideration of attribute alignment in Emich et al. (2022) to more than two attribute vectors by taking the mean square distance between attribute vectors. This can be defined as: $\frac{1}{v}(\delta_1 + ... + \delta_v)$ or $\frac{1}{v}\sqrt{(\delta_1 + ... + \delta_v)}$.

Appendix B: Physics-Based Approach: The Derivation of Potential Energy as an Alignment Measure

The electrostatic potential energy caused by two point charges has the form $U = C\frac{\gamma_1\gamma_2}{r}$ for $C > 0$, where U represents the potential energy of the system, C is some constant, γ_1, γ_2 are the magnitude of the point charges, and r is the Euclidean distance between the charges. For simplicity, we set $\gamma_1 = \gamma_2 = C = 1$ since, in our context, there is no reason that one attribute vector should be of higher magnitude than another should. Then we adopt the principle of superposition, which states that the total potential energy of a system of point charges is the sum of the energy resulting from each pair of point charges. Thus, we denote the total potential energy of the system of attribute vectors as: $U(x_1,...,x_a) = \sum_{i=1}^{a}\sum_{j=i+1}^{a} \left\|x_i - x_j\right\|^{-1}$, where $x \in R^d$ represents attribute vectors of length d and a is the number of attribute vectors in the system[3].

As in Emich et al. (2022), the potential energy quantity inherits certain desirable properties including symmetry (all attributes contribute to the alignment value in the same way) and permutation invariance (there is no preferred ordering among team members). In addition, like Emich et al. (2022), we propose several modifications to the base quantity $U(x_1, \dots, x_a)$ to allow researchers to effectively use this approach when studying multiple attributes in teams.

The first modification is inherited from Emich et al. (2022), and involves normalizing the Euclidean distance to account for varying team size d across the different teams being studied. To do this, we multiply distances by the quantity $1/\sqrt{d}$, resulting in:

$$\sum_{i=1}^{a}\sum_{j=i+1}^{a} \left[\left\|x_i - x_j\right\| / \sqrt{d}\right]^{-1}.$$

[3] This norm, and all norms referenced in this article, is the Euclidean norm (2-norm).

This modification acts to normalize the maximum distance between points, ensuring that the distance from a vector of all zeros to a vector of all ones is the same regardless of team size.

The second modification enforces a minimum distance between points, or attributes. This is motivated by the unbounded nature of the potential energy: if any points exist in the same space (i.e., no distance between attribute vectors), their potential energy goes to infinity. Although this is unlikely to be a practical issue, if we consider all points at least some minimum distance from each other then the potential energy generated by any pair of points has a maximum value. We assume that attribute vectors are observed with measurement error, or under the presence of Gaussian noise[4] - x is observed as $x + \epsilon$ for $\epsilon \sim N(0, \sigma^2 I_d)$.

As such, the distance between two vectors satisfies $\left\|x_i - x_j\right\| = \left\|\left(x_i + \varepsilon_i\right) - \left(x_j + \varepsilon_j\right) - \left(\varepsilon_i - \varepsilon_j\right)\right\| \geq \left\|\left\|\left(x_i + \varepsilon_i\right) - \left(x_j + \varepsilon_j\right)\right\| - \left\|\left(\varepsilon_i - \varepsilon_j\right)\right\|\right\|$, where we have invoked the triangle inequality[5]. So, even if we observe that $\left\|x_i + \varepsilon_i - \left(x_j + \varepsilon_j\right)\right\| = 0$, the presence of any noise means that we should not expect precision at a level beyond $\left\|x_i - x_j\right\| \geq \left\|\varepsilon_i - \varepsilon_j\right\|$. We know that $\varepsilon_i - \varepsilon_j \sim N(0, 2\sigma^2 I_d)$ (is normally distributed with mean 0 and covariance $2\sigma^2 I_d$ where I_d is the *d*-dimensional identity matrix), so $\left\|\varepsilon_i - \varepsilon_j\right\| / (\sqrt{2\sigma}) \sim \chi_d$ follows a Chi distribution with *d* degrees of freedom (Forbes et al., 2011). The expected value $E\left[\left\|\varepsilon_i - \varepsilon_j\right\|\right] = \sigma\Gamma((d+1)/2) / \Gamma(d/2) \equiv \sigma\tau_d$, where we define $\tau_d = \Gamma((d+1)/2) / \Gamma(d/2)$ for compactness. This gives us a reasonable guideline for the minimum distance. We apply this in conjunction with the team size scaling to further adjust our sense of global alignment to:

[4] This Gaussian assumption is for simplicity and could easily be replaced by another distribution.
[5] The sum of the lengths of any two sides must be greater than or equal to the length of the remaining side.

$$\sum_{i=1}^{a} \sum_{j=i+1}^{a} \left[\max(\left\| x_i - x_j \right\|, \sigma\tau_d / \sqrt{d}) \right]^{-1}.$$

The σ quantity must be chosen by the researcher. In principle, this quantity would be determined from an analysis of the circumstances under which attribute values were collected to represent the uncertainty with which this collection took place. In practice, less demanding, more empirical strategies exist for choosing σ. In circumstances with discrete-valued attributes (such as integers), σ should be chosen as half the value of the smallest nonzero distance (i.e., 0.5, in the case of integers). For example, when using a 1-5 or 1-7 integer scale to measure attributes, researchers should set the minimum distance, σ, to 0.5. An analogous strategy for attributes with continuous values might be to jointly analyze the pairwise distances associated with each team and choose a distance below which differences are considered too small to differentiate, such as .001 in most cases. This can only be determined on a study-by-study basis using observed values to ascertain what σ value is appropriate.

The third modification is to aid the interpretation of the potential energy-based alignment scores. We scale the global alignment so it always takes values between 0 and 1. The minimum value is already 0, which will occur only when all attributes are infinitely far away from each other. To scale the maximum alignment to 1, we note that there are $v_a = \frac{1}{2} a(a-1)$ total entries in potential energy summation. Because we have defined a minimum distance, we know that the maximum value associated with each term in the summation is $\sqrt{d} / (\sigma\tau_d)$. As such, the maximum value associated with the summation is $v_a \sqrt{d} / (\sigma\tau_d)$, and we can divide by this quantity to set the maximum global alignment to 1:

$$\frac{\sigma\tau_d}{v_a \sqrt{d}} \sum_{i=1}^{a} \sum_{j=i+1}^{a} \left[\max(\left\| x_i - x_j \right\|, \sigma\tau_d / \sqrt{d}) \right]^{-1}.$$

At this point, we recognize that the team size scaling we have imposed on the distances cancels out the scaling imposed to bound the global alignment to [0,1], leaving us with our *final physics-based definition of global alignment through potential energy*:

$$\frac{\sigma\tau_d}{v_a}\sum_{i=1}^{a}\sum_{j=i+1}^{a}\left[\max(\left\|x_i - x_j\right\|, \sigma\tau_d)\right]^{-1} \quad (1)$$

Appendix C: Algebraic Approach: The Derivation of Singular Value Decompositions (SVD) as an Alignment Measure

To define an algebraic solution to considering attribute alignment, we start by organizing the attribute vectors into a matrix as follows,

$$\mathrm{X} = \begin{pmatrix} \boldsymbol{x}_1 & \cdots & \boldsymbol{x}_a \end{pmatrix}$$

We denote the singular values of this matrix to be $\lambda_1, \lambda_2, \ldots, \lambda_a \geq 0$, organized in descending order. Using these, we define an algebraic sense of global alignment to be

$$S(\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n) = \frac{1}{\|\mathrm{X}\|_F} \frac{\lambda_1}{\lambda_2}, \qquad \mathrm{X} = \mathrm{U} \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_a \end{pmatrix} \mathrm{V}^T$$

where the matrix norm is the Frobenius norm (equivalent to the 2-norm of the singular values) and U and V are unitary matrices that are not used in our computation. The ratio of the top two singular values will tend to 1 if there is a stark difference between at least two of the attribute vectors; and, it will tend towards infinity as all of the attribute vectors look more and more like each other (there is maximum alignment). Dividing by the matrix's Frobenius norm allows us to account for team size, which is similar to our strategy when considering geometric global alignment.

It should be noted that this quantity, at present, is unbounded and will require a modification to deal with the situation where the second largest singular value tends to 0 – this is similar to the situation involving minimum distance that earlier appeared in the physics-based global alignment.

Appendix D: Empirical Example of the Alignment of Three or More Attributes

In line with recommendations in response to Question 7, we now provide an empirical example, using field data, to address an attribute alignment question. First, we theoretically define our attribute system as pertaining to conscientiousness, openness, and agreeableness.

To do this, we begin with conscientiousness, the tendency to be determined, organized, purposeful, and deliberate (Costa & McCrae, 2008). Conscientiousness is considered a powerful personality trait in the literature pertaining to work and organizational settings (Tang et al., 2021), and is consistently linked to effective individual performance (e.g., Barrick & Mount, 1991; Hogan & Kaiser, 2005; Li et al., 2014). However, conscientiousness has two potential drawbacks for team performance. First, conscientiousness does not seem to benefit performance on tasks requiring creativity or adaptation (Moynihan & Peterson, 2001; Robert & Cheung, 2010), perhaps because conscientious individuals prefer structured and systematic goals and tasks (Colbert & Witt, 2009; Neuberg & Newsom, 1993; Tang et al., 2021). Yet, many of the most pressing and outstanding organizational problems require creativity and adaptation by the teams that are tasked with addressing them (Hall et al., 2018). Second, conscientious individuals do not necessarily have strong team orientation (Barrick et al., 1998; Mohammed & Angell, 2003), which means their focus on task completion may be individualistic and self-oriented, not collaborative (Anderson et al., 2008; Moon et al., 2013).

This suggests that the coexistence of other personality factors may be important to capitalize on the potential benefits of conscientiousness. Particularly, openness, or the tendency to be curious and interested in new ideas and experiences (Costa & McCrae, 2008), could address the potential for too much structure or lack of innovation. Similarly, agreeableness, or the tendency to cooperate and prioritize interpersonal relationships in group settings (Graziano &

Eisenberg, 1997), could provide the team orientation needed to include other team members in the achievement of collective goals (Mohammed & Angell, 2003). As such, we suggest that as conscientiousness, openness, and agreeableness become more aligned, team performance may increase.

Next, we need to choose a method for calculating the alignment of these three attributes. The geometric approach using the average distance, the approach recommended for most alignment questions, will work well for our hypothesis as it allows each pairwise alignment between conscientiousness, openness, and agreeableness to be reflected equally in a global alignment score. We have no reason to believe that a very short pairwise distance between any of these attributes should be more influential in a global alignment score, or that these three attributes must be perfectly aligned to effect team performance, or that the system as a whole should be considered more aligned if they are perfectly aligned. We therefore do not necessarily need the physics approach. There is also no reason for us to believe the shape or direction of alignment alone (and not the magnitude) should account for this effect, and we are able to ensure that these attributes are measured on similar scales and can be transformed appropriately for calculating alignment (see the 'Measures' section below). We therefore do not need to use the algebraic approach. Thus, we choose the average distance as our analysis method.

Participants and Procedure

Our sample consists of 777 MBA students participating in an ongoing data collection effort at a graduate business school in the United Kingdom. These participants were assigned to 126 teams of between five and eight members ($M = 6.12$, $SD = .76$) at the start of their first year in the program and were kept intact for one calendar year. Participants were assigned to their teams to maximize functional expertise diversity and nationality. Participants represented 74

countries led by the United States (11.58%), the United Kingdom (9.65%), India (7.21%), and Australia (5.79%), and 577 companies across 60 industries. Their average age was 28.66 years (*SD* = 2.49), 68% were male, and 45% were White. They had average work experience of 5.56 years (*SD* = 1.97). Before starting the MBA program, participants completed our personality measure, described below. We collected our team performance measure after the students worked together for seven months.

Measures

Conscientiousness, Openness, and Agreeableness. We measured conscientiousness, openness, and agreeableness using the 240-item NEO-PIR Inventory (Costa & McCrae, 2008) of which 48 items measured each attribute: conscientiousness (α =.90), openness (α = .87), agreeableness (α = .87). Responses were indicated on a five-point Likert-type scale from "*Strongly Disagree*" to "*Strongly Agree*".

Importantly, because an initial Levene's test indicated differences in sample variances, $F = 4.65$, $p = .01$, such that conscientiousness had more variance (*SD* = .39) than openness (*SD* = .36) or agreeableness (*SD* = .34), we used a linear transformation to adjust conscientiousness scores by the ratio of this difference before calculating alignment (Emich et al., 2022). This resulted in equal variances among attributes, $F = 1.49$, $p = .23$, and ensured no attribute accounted for alignment more than the others did, preserving the assumption of symmetry.

Attribute Alignment. We use the average distance measure described above.

Team Performance. We measured team performance using team grades on their collective midterm examination in their Organizational Behavior course. This examination involved completing a timed, in-class case analysis where teams needed to work collaboratively to apply multiple theoretical perspectives to address a complex organizational problem. Scores

comprised one-third of students' course grade and were out of 100 points (M = 81.75, SD = 4.71, *Max.* = 93.00).

Results

Descriptive statistics and correlations among our focal variables can be found in Table D1. In it, one can clearly see that although the three pairwise alignments that comprise the C-O-A attribute system are moderately correlated (between r = .10 and r = .31), they are not equivalent constructs. However, the relationships between these 2-attribute alignments and C-O-A alignment are highly correlated (between r = .66 and r = .81) as they comprise the same pairwise distances, as discussed in response to Question 5.

To test our hypothesis that C-O-A alignment leads to higher team performance, we would simply regress performance onto C-O-A alignment. In doing so, we would discover that this alignment type indeed negatively and significantly relates to team performance in this context (β = -.23, t = -2.31, p = .02), predicting 4% of the variance in it. This would provide support for our hypothesis since it would indicate that smaller distances between the attributes (more alignment) increases team performance.

Additionally, based on prior work (e.g., Barrick et al., 1998) we may expect that mean levels of these attributes account for variance in team performance. In this case, these could be added to the model as control variables, but they are not necessary elements of a model testing alignment effects. Using this sample, including means of these attributes does not eliminate the relationship between C-O-A alignment and team performance, β = -.26, t = -2.54, p = .01.

However, if we were interested in assessing whether any single pairwise distance accounted for this effect, we could regress team performance onto C-O, C-A, and O-A alignment in a separate model. In doing so, we would discover than none (C-O alignment: β = -.13, t = -

1.34, p = .18, C-A alignment: β = -.10, t = -1.08, p = .28, O-A alignment: β = -.05, t = -.58, p = .57) predicted team performance in this model. This would indicate that, although C-O alignment negatively correlates with team performance, it does not predict performance in the context of this attribute system. We would not recommend exploring whether C-O alignment alone predicts performance because the original hypothesis includes all three attributes as relevant to a system of attributes that would influence team performance. Testing C-O without agreeableness would not account for the theoretical importance of agreeableness in conjunction with conscientiousness and openness, restricting the hypothesized system.

Additionally, although we did not predict that mean levels of these attributes would interact with C-O-A alignment to predict team performance, we could test this in considering the robustness of our effect. In doing so, we would follow standard procedure and mean-center both attribute alignment and mean values before calculating their product. We did this for mean levels of each attribute considered and found that none interacted with C-O-A alignment to predict team performance (mean conscientiousness interaction: t = -.89, p = .38, mean openness interaction: t = .58, p = .56, mean agreeableness interaction: t = -.71, p = .48). This indicates that, in our data, no threshold exists below which this alignment did not matter. This is most likely due to the fact that our sample comes from an elite MBA program where most students are at least moderately conscientious and open. Therefore, it is unlikely that we would find a team of people who are all low on all attributes and indeed, we had no such teams in our data.

Interpretation

Based on our findings, we would interpret that the more conscientiousness, openness, and agreeableness exist in some team members relative to others, the better the team performs.

Table D1

Means, standard deviations, and correlations focal team-level variables

Variable	Mean	SD	1	2	3	4	5	6	7
1. Team C Mean	3.45	0.15	-----						
2. Team O Mean	3.57	0.15	-.01	-----					
3. Team A Mean	3.41	0.13	.04	.01	-----				
4. Team C-O Alignment	0.50	0.17	.52**	.18*	-.03	-----			
5. Team C-A Alignment	0.43	0.13	-.08	.08	-.26**	.29**	-----		
6. Team O-A Alignment	0.47	0.13	-.12	.40**	-.25**	.31**	.10	-----	
7. Team C-O-A Alignment	0.47	0.10	-.38**	.31**	-.23**	.81**	.62**	.66**	-----
8. Team Performance	81.74	4.71	.08	.05	.01	-.18*	-.14	-.10	-.20*

Note. C = Conscientiousness. O = Openness. A = Agreeableness. *$p < .05$ ** $p < .01$.

Appendix E: Python Code for Calculating the Alignment of Three or More Attributes

To access our Python and R code, please visit: https://github.com/kjem514/Attribute-Alignment-Code and read the README.md file.

We also provide an explanation of our Python code here. One may calculate the metrics described in this paper (average distance, potential energy of the system, SVD) by using the following code in Python 3.5.

First, run the following to set up your data:

```
import pandas
import numpy as np
from scipy.spatial.distance import cdist
from scipy.stats import linregress
from scipy.special import gamma
from itertools import permutations, combinations
import matplotlib.pyplot as plt
%matplotlib inline

# MINIMUM_DISTANCE_BASE is a quantity that helps make sure the difference between two vectors is never actually 0
# This is a reasonable assumption under the belief that observations are made in the presence of noise
# If we actually knew the distribution of the noise we could set this in an informed fashion
# Without that, we can simply set this to a "small" number and then play around with it
MINIMUM_DISTANCE_BASE = .001

# Set TEAM_SIZE_SCALING = True to allow for the distance between larger teams to be scaled down
TEAM_SIZE_SCALING = True

def extract_columns(columns, all_data, team_id_name='OverallGroupID', outcome_column_name=None):
    data_matrix = all_data.values
    team_id_index = np.where(imported_data.columns == team_id_name)[0][0]
    if outcome_column_name:
        outcome_index = np.where(imported_data.columns == outcome_column_name)[0][0]
```

```
    results = {}
    for row_num, row in enumerate(data_matrix):
        team = int(row[team_id_index])
        if team not in results:
            results[team] = {'attribute_dict': {column: [] for column in columns}}
        if outcome_column_name:
            results[team][outcome_column_name] = row[outcome_index]
        for column in sorted(columns):
            results[team]['attribute_dict'][column].append(all_data[column][row_num])
        results[team]['attributes'] = np.array([results[team]['attribute_dict'][column] for column in columns]).T

    return results

def _determine_auxiliary_terms(attributes, minimum_distance_base, team_size_scaling):
    d = len(attributes)
    team_size_scaling_value = 1 / np.sqrt(d) if team_size_scaling else 1.0
    minimum_distance = minimum_distance_base * gamma((d + 1) / 2) / gamma(d / 2) * team_size_scaling_value
    return minimum_distance, team_size_scaling_value
```

Then, run the following to compute average distance among attribute vectors:

```
def compute_average_distance(attributes, minimum_distance_base=MINIMUM_DISTANCE_BASE, team_size_scaling=TEAM_SIZE_SCALING):
    minimum_distance, team_size_scaling_value = _determine_auxiliary_terms(attributes, minimum_distance_base, team_size_scaling)
    distance_matrix = cdist(attributes.T, attributes.T)
    d = np.fmax(distance_matrix * team_size_scaling_value, minimum_distance)
    distances = d[np.where(np.triu(d, 1))]
    return 1 / len(distances) * np.sum(distances)
```

If you are instead interested in calculating the potential energy of the system, run the following:

```
def compute_potential_energy(attributes, minimum_distance_base=MINIMUM_DISTANCE_BASE, team_size_scaling=TEAM_SIZE_SCALING):
    minimum_distance, team_size_scaling_value = _determine_auxiliary_terms(attributes, minimum_distance_base, team_size_scaling)
    distance_matrix = cdist(attributes.T, attributes.T)
    d = np.fmax(distance_matrix * team_size_scaling_value, minimum_distance)
    distances = d[np.where(np.triu(d, 1))]
    return minimum_distance / len(distances) * np.sum(1 / distances)
```

If you are interested in calculating the SVD of the system, run the following:

```
def compute_svd_alignment(attributes, minimum_distance_base=MINIMUM_DISTANCE_BASE, team_size_scaling=TEAM_SIZE_SCALING, num_draws=50, max_draws=10000):
    minimum_distance, _ = _determine_auxiliary_terms(attributes, minimum_distance_base, team_size_scaling)

    # The team size is already accounted for in the Frobenius norm
    # If we want to shut off the impact of team size, we multiply back in the
    def _svd_alignment(x):
        singular_values = np.linalg.svd(x, compute_uv=False)
        team_size_scaling_value = (1.0 if not team_size_scaling else len(x)) / np.linalg.norm(x, ord='fro')
        return singular_values[0] / singular_values[1] * team_size_scaling_value

    # Technically, the restriction to all positive values isn't necessary, but I think it makes sense
    # The random_shift goes up to 2 * minimum_distance to allow a decent potential of convergence even for high alignment
    vals = []
    for _ in range(max_draws):
        random_shift = np.random.uniform(-1, 1, size=attributes.shape)
        random_shift = np.random.uniform(0, 2 * minimum_distance) * random_shift / np.sqrt(np.sum(random_shift ** 2, axis=0)[None, :])
        shifted_attributes = np.fmax(attributes + random_shift, 0)
        distance_matrix = cdist(shifted_attributes.T, shifted_attributes.T)
        distances = distance_matrix[np.where(np.triu(distance_matrix, 1))]
        if not all(distances > minimum_distance):
            continue

        vals.append(_svd_alignment(shifted_attributes))
        if len(vals) >= num_draws:
            break
    else:
        raise ValueError('SVD alignment falied to converge')

    return np.mean(vals)
```

To print and save these values, run the following:

```
def add_metrics(info, minimum_distance_base=MINIMUM_DISTANCE_BASE, team_size_scaling=TEAM_SIZE_SCALING):
    for team_id, stuff in info.items():
        attributes = stuff['attributes']
        stuff['metrics'] = {
            'energy': compute_potential_energy(attributes, minimum_distance_base, team_size_scaling),
            'avg_dist': compute_average_distance(attributes, minimum_distance_base, team_size_scaling),
            'svd': compute_svd_alignment(attributes, minimum_distance_base, team_size_scaling),
            'pairwise': compute_pairwise_distances(attributes, minimum_distance_base, team_size_scaling),
        }

def print_metrics(info, team_id_name='OverallGroupID', outcome_column_name='outcome', savefile=None, csv_sep='\t', suppress_output=False):
    header_printed = False
    lines = []
    def print_maybe(string):
        if not suppress_output:
            print(string)

    for team_id, stuff in info.items():
        if not header_printed:
            attribute_names = [attribute for attribute in sorted(stuff['attribute_dict'].keys())]
            metric_names = [metric for metric in sorted(stuff['metrics'].keys()) if metric != 'pairwise']
            s = [team_id_name, outcome_column_name]
            s += metric_names
            if 'pairwise' in stuff['metrics']:
                for attribute_1, attribute_2 in combinations(attribute_names, 2):
                    s.append('--'.join(['pairwise', attribute_1, attribute_2]))
            s = csv_sep.join(s)
            print_maybe(s)
            lines.append(s)
            header_printed = True
        s = [team_id, stuff[outcome_column_name]] + [stuff['metrics'][metric] for metric in metric_names]
        s += stuff['metrics']['pairwise'].tolist()
        s = csv_sep.join((str(ss) for ss in s))
        print_maybe(s)
        lines.append(s)

    if savefile:
        with open(savefile, 'w') as f:
            f.writelines(l + '\n' for l in lines)
```

Finally, if you are interested in printing the values to either a separate file or this file, you can do so by using the following:

```
outcome_column_name = 'DV'
attributes_to_study = ('attribute_0', 'attribute_1', 'attribute_2', 'attribute_3')

imported_data = pandas.read_csv('my-data-file.csv', index_col=False, sep=',')
results = extract_columns(attributes_to_study, imported_data, outcome_column_name=outcome_column_name)
add_metrics(results)
# Set suppress_output=False to print to screen
print_metrics(results, savefile='where-i-store-alignment-values.csv', suppress_output=False, outcome_column_name=outcome_column_name)
```

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