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Multilevel Methods for Emergent Processes in Teams

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Abstract

Teams are dynamic systems that develop, adapt, and change as members interact and respond to their environments. Theory in organizational research emphasizes that team phenomena are multilevel, temporal, and often nonlinear. Yet, the statistical methods commonly used to study teams have lagged behind these theoretical advances, limiting empirical progress. This dissertation addresses this methodological shortcoming through three papers.

In Paper I, we critically examine existing approaches to the empirical estimation of consensus emergence, the process through which initially diverse individual perceptions converge into a shared team perspective. We introduce a formal statistical definition of consensus emergence and demonstrate common pitfalls, such as conflated variance components and model misspecification.

In Paper II, we extend heterogeneous variance models by integrating Gaussian processes. This framework provides a flexible way to capture nonlinear changes in variability over time, thereby allowing richer insights into how convergence and divergence unfold within teams.

In Paper III, we turn to the evolution and consequences of emergent states. Using the development of new venture teams as an empirical context, we propose a joint modeling framework to study how trust trajectories are shaped by significant events and, in turn, how trust predicts member departure. The model further accounts for non-ignorable missing data through a shared-parameter specification.

Together, these contributions advance the methodological toolkit for studying emergent team phenomena. By aligning statistical models more closely with theoretical advances, the dissertation provides researchers with tools to rigorously examine how collective states form, evolve, and influence outcomes in dynamic organizational settings.

Key words

group dynamics, emergent states, heterogeneous variance models, multilevel, Gaussian Processes, joint models

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Contents

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Yvette Baurne
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Abstract

Teams are dynamic systems that develop, adapt, and change as members interact and respond to their environments. Theory in organizational research emphasizes that team phenomena are multilevel, temporal, and often nonlinear. Yet, the statistical methods commonly used to study teams have lagged behind these theoretical advances, limiting empirical progress. This dissertation addresses this methodological shortcoming through three papers.

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Popular Science Summary

We spend much of our lives in groups - families, school classes, sports teams, or work projects. Teams, in particular, are central to modern organizations. They are not static entities: trust can build or erode, members can leave or join, and events can strengthen or disrupt collaboration. Understanding these dynamics is crucial but studying them is challenging. The dynamics are complex, they change over time, do not progress smoothly, and they often look different across individuals and teams.

This thesis develops new statistical methods to help researchers better capture how teams evolve. The first part focuses on how shared team states, such as team trust or team cohesion, are formed. Researchers often assume that individuals in a team gradually converge toward a common perspective, but current statistical measures can give misleading results about whether this is happening or not. We propose a new way of defining and estimating these processes, which avoids several common pitfalls.

The second part addresses how team dynamics unfold over time. Using advanced tools from machine learning, we develop methods that allow for nonlinear patterns such as rapid increases followed by plateaus, which traditional models cannot capture. These methods also make it possible to study how variability itself changes, for example, whether team members are becoming more similar or more different over time.

The third part investigates what happens once a shared state has formed. We study trust in entrepreneurial teams, showing how significant events can disrupt or strengthen trust, and how trust influences whether members stay or leave. To do this, we combine models for changes over time with models for discrete events, while also accounting for the fact that survey responses are often missing in ways that are not random.

Altogether, the thesis shows how more flexible and precise statistical methods can provide deeper insights into how teams function, adapt, and sometimes fall apart. These tools bring researchers closer to answering important questions about collaboration in organizations. These questions matter not only for research but also for practice in workplaces where teamwork is essential.

List of Publications

This thesis is based on the following papers, referred to by their Roman numerals:

I **Empirical Estimation of Consensus Emergence: Progress, Pitfalls, and the Path Forward**
Yvette Baurne, Frédéric Delmar, and Jonas Wallin
Preprint, 2025.

II **Heterogeneous Variance Models with Gaussian Processes**
Yvette Baurne, Frédéric Delmar, and Jonas Wallin
Submitted to Psychological Methods, 2025.

III **How Significant Events and Team Trust in New Venture Teams Predict Member's Departure**
Yvette Baurne, Frédéric Delmar, and Jonas Wallin
Preprint, 2025.
A previous version of this paper was presented at the Academy of Management 2023, Boston, USA:
Baurne, Y., Delmar, F., Wallin, J., & Brattstrom, A. (2023). How Significant Events and Team Trust Predict Member's Exit in New Venture Teams. In Academy of Management Proceedings (Vol. 2023, No. 1, p. 11742). Briarcliff Manor, NY 10510: Academy of Management.

1. Introduction

Humans tend to organize themselves in groups. We live in families, go to school where students are gathered in classes, join teams at work, and often identify with broader communities such as hobby groups or sports clubs. Exactly what constitutes a group has been debated among social psychologists (see, e.g., Brown and Pehrson (2020) and Forsyth (2018)), but here we adopt the broad definition that a group is "two or more individuals who are connected by and within social relationships" (Forsyth, 2018, p. 27). Group research spans many fields in the social sciences, encompassing interests at the individual level, the group level, and the interplay between them. The unifying interest lies in *group dynamics*; the scientific study of the processes that unfold within and between groups over time (Forsyth, 2018). These processes shape how members relate to one another, how groups respond to their environments, and ultimately what they achieve.

Within this broad landscape of group dynamics, this dissertation focuses on *teams* in organizational contexts. Teams are dynamic social systems: they form, develop, and adapt as members join and leave, as roles and norms evolve, and as the external environment shifts. To capture these complexities, organizational researchers increasingly rely on multilevel theories that link individual behaviors, team-level properties, and broader contextual factors (Mathieu et al., 2017). Such theories emphasize that teams are embedded in time: team properties and processes emerge, evolve, and change in response to both internal interactions and external demands. Yet, despite this recognition, the statistical methodologies available to study temporal dynamics in teams have not kept pace with theoretical developments (Eckardt et al., 2021; Kozlowski & Chao, 2018; Marks et al., 2001). This creates a growing gap between theoretical ambition and empirical practice.

A central distinction in the team literature is between *processes* and *emergent states*. Processes are the interdependent actions through which members coordinate, monitor, and regulate their joint work, whereas emergent states are cognitive, motivational, and affective properties of the team that arise from interactions and in turn influence subsequent processes (Marks et al., 2001; Mathieu et al., 2017). Examples of emergent states include cohesion, trust, and shared mental models. These constructs are not static: they vary as a function of prior experiences and team context, and they can shift rapidly in response to events. Team research therefore often examines both the temporal unfolding of emergent states and the feedback loops between states and processes (Mathieu et al., 2017).

Emergent states can arise through different forms of emergence, most commonly described as *composition* and *compilation* (Kozlowski & Chao, 2018; Kozlowski & Klein, 2000). In composition emergence, individual attributes or perceptions converge over time as members share experiences and interact in a common context. The result is a shared property at the team level, often captured by the aggregation of member responses. The process that creates these shared properties is called *consensus emergence*. Classic examples of composition emergent states include cohesion or climate, where convergence in perceptions reflects a genuine team-level state. In contrast, compilation emergence reflects the integration of differentiated, rather than convergent, individual contributions. Here, a team-level property arises from a patterned configuration of diverse inputs across members. For example, a transactive memory system emerges when members develop specialized knowledge and a shared understanding of "who knows what." Both forms of emergence are central to team functioning, yet they pose different theoretical and methodological challenges: composition requires modeling convergence and agreement over time, whereas compilation requires attention to patterns, networks, and distributions across members.

Once higher-level properties emerge, they can shape behavior through both bottom-up and top-down processes (Kozlowski & Chao, 2018). Concepts such as trust, cohesion, and consensus emergence illustrate why temporal, multilevel thinking is essential. Trust, for instance, is theorized to emerge from interpersonal interactions, to evolve dynamically over time, and to influence key outcomes such as performance and member retention (Costa et al., 2018). Although trust is recognized as dynamic, most empirical work has relied on static or cross-sectional designs. There is a need for longitudinal research that investigates how trust evolves over time, what predicts transitions between stages of trust development, and how trust at different stages relates to team outcomes (Costa et al., 2018).

Despite these theoretical advances, there remains a significant methodological gap. Current statistical approaches often treat dynamic constructs as if they were static, rely on overly simplistic aggregation with a heavy focus on means and correlations, or impose (too) restrictive assumptions of linearity (Eckardt et al., 2021; Kozlowski & Chao, 2018; Mathieu et al., 2017).

We can divide research on emergence into two complementary areas. The first concerns *how emergent states come to be*: how individual-level perceptions and behaviors interact to form higher-level team properties, whether through composition or compilation. The second concerns *what happens once emergent states exist*: how these dynamic constructs evolve over time, what predicts their trajectories, and how they relate to important outcomes. Both perspectives require methodological advances.

Methods for disentangling consensus emergence from other parallel processes are still underdeveloped (Dishop, 2022; Lang et al., 2019), and the models commonly used in practice lack the flexibility to capture the nonlinear and discontinuous changes that characterize many psychological phenomena (Failenschmid et al., 2025; Vowels, 2023). On top of these challenges, the practical realities of survey-based longitudinal research such as participant fatigue, non-ignorable missing data, and arbitrary time intervals, further complicate inference (Daniels & Hogan, 2008; Kozlowski & Chao, 2018). Taken together, these limitations mean that multilevel theory has advanced more rapidly than available methodology, leaving key theoretical propositions empirically underexamined.

To model emergence, we need methods that can separate the focal construct from other parallel processes, account for multilevel dependence, and represent nonlinear trajectories. To model the evolution of team dynamics, we need longitudinal frameworks that can capture dynamic change, link to outcomes, and handle missingness appropriately. Such methodological advances are required for the progression of the research field.

In sum, team research is motivated by rich theoretical questions about emergent and evolving collective phenomena. Yet to realize this ambition, statistical methods must advance to capture the multilevel, temporal, and nonlinear nature of the data, and to guard against conflated processes and spurious conclusions. The methodological contributions of this dissertation are directed at closing that gap.

Paper I and II are devoted to methods for composition emergence. In the first paper, we take measure of existing methods for consensus emergence and illustrate common pitfalls, for instance caused by utilizing methods for static constructs on dynamic constructs, or misspecified models that fail to account for dynamics present in data. In the second paper, we extend commonly used multilevel models to allow for nonlinear change by combining them with Gaussian processes, which gives a flexible approach that allows deeper insights into the process of consensus emergence. The third paper is devoted to the modeling of trajectories of dynamic concepts over time, how they are affected by events, and how they relate to other outcomes of interest.

The remainder of the thesis is structured as follows. The next section outlines the statistical foundations that underpin the work presented in the three papers. This is followed by a summary of the papers themselves, and the thesis ends with conclusions and an outlook for future research.

2. Background

The introduction outlined a central gap in team research: theory emphasizes that many team phenomena are dynamic, multilevel, and often nonlinear, yet many of the statistical methods commonly applied does not account for this. Here we review the foundations of the statistical methods on which the contributions of this dissertation builds. Each subsection introduces a key class of models, starting with multilevel models as the baseline framework, then extending to approaches that allow heterogeneous variances, nonlinear trajectories, and the integration of longitudinal processes with discrete events and missing data. Together, these methods illustrate how increasingly flexible models can better capture the complexities of group dynamics.

2.1 Multilevel Models

To begin, we consider how to handle the nested structure of group data. When studying group dynamics, data are typically *nested*: repeated observations are collected from individuals, and those individuals belong to groups such as teams or school classes. This creates dependencies: observations from the same person are correlated, and people from the same team share experiences that also make their responses correlated. Standard linear regression models assume that residuals are independent. When this assumption is violated, as in nested data, the residuals are positively correlated and the model effectively treats dependent observations as if they were independent. This leads to underestimated standard errors and inflated Type I error rates (Raudenbush, 2002; Snijders & Bosker, 2011).

Multilevel models, also known as mixed effects models, hierarchical linear models, or random effects models, were developed to address this issue (Goldstein, 2011; Raudenbush, 2002; Snijders & Bosker, 2011). They provide a principled way to account for dependencies by including random effects at each relevant level of the hierarchy.

A basic three-level model can be specified as follows:

$$\begin{aligned} y_{tij} &= \mathbf{x}'_{tij}\boldsymbol{\beta} + \tau_{0j} + v_{0ij} + e_{tij}, \\ \tau_{0j} &\sim N\left(0, \sigma^2_{\tau 0}\right),\ v_{0ij} \sim N\left(0, \sigma^2_{v0}\right),\ e_{tij} \sim N\left(0, \sigma^2_{e}\right). \end{aligned} \tag{2.1}$$

Here, y_{tij} is the response at time t for person i in group j, where $t = 1, \ldots, T_i$, $i = 1, \ldots, m_j$, $j = 1, \ldots, J$. The model contains a set of fixed effects $\mathbf{x}'_{tij}\boldsymbol{\beta}$, a group-specific random effect τ_j, an individual-specific random effect v_{ij}, and a residual term e_{tij}. Each random effect is assumed independent and normally distributed with mean zero and constant variance. The group-level random effect τ_j captures similarities among members of the same group, reflecting shared experiences or environments (for example, a common leadership style or group climate). The individual-level random effect v_{ij} captures similarities among repeated measures from the same person, reflecting person-specific tendencies such as being generally more or less trusting. By including both group- and individual-level random effects, the model accounts for the dependencies inherent in nested data: observations are no longer incorrectly treated as independent, but their correlation structure is explained by shared latent components at the relevant levels (Goldstein, 2011; Snijders & Bosker, 2011).

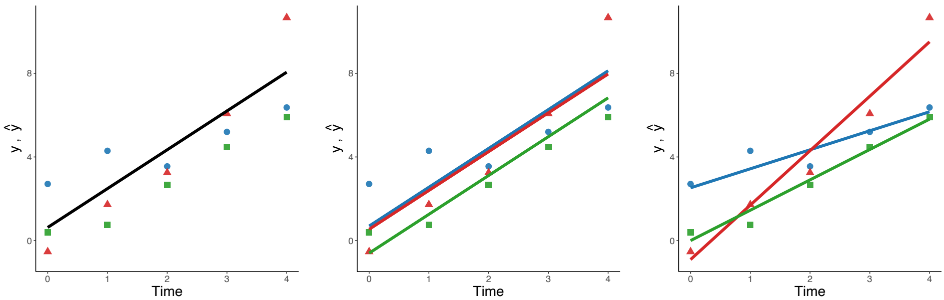
The random effects specified above are also know as random intercepts, which can be interpreted as individual or group-specific deviations from the fixed intercept β_0. The model can also include random slopes. For example, one may allow different individuals within a class to have different learning trajectories by including $t_{tij}\mathbf{v}_{ij}$ in the model. This way, we can study both the global average change over time and how individuals deviate from it, some with steeper or flatter trajectories. Similarly, one can allow for different group trajectories by including $t_{tij}\tau_j$, introducing random slopes at the group level.

Example. Imagine we want to study how *team trust* among individuals within a group develops over time. A classic linear regression would fit a single straight line, describing the average change across all individuals and ignore the nested dependency structure of repeated observations of individuals. In reality, individuals may differ: some begin with higher or lower trust (different intercepts), and some build trust faster than others (different slopes). A random intercept allows each person to start at their own baseline trust level, while a random slope allows for individual differences in how trust changes over time.

Figure 2.1 illustrates this idea. All three plots show observations from the following multilevel model:

$$
\begin{aligned}
y_{tij} &= \beta_1 t + v_{0ij} + v_{1ij} t + e_{tij}, \\
v_{0ij} &\sim N\left(0, \sigma^2_{v0}\right),\ e_{tij} \sim N\left(0, \sigma^2_e\right)
\end{aligned}
$$

We then fit three models to this data; a standard linear regression model with only fixed effects, a multilevel model with random intercepts, and finally a multilevel model with both random intercept and slope. The figures show the fitted regression lines $\widehat{y}_{tij}$, and colored dots for three different individuals. Figure 2.1a show the population-level fitted trajectory, which is the same for all individuals. Figure 2.1b show subject specific fitted trajectories (using best linear unbiased predictors, BLUPs (C. R. Henderson, 1975)) of the random intercepts. Here the model allows for different initial levels of trust but assumes the same trajectory over time, seen by the parallel lines. Finally, Figure 2.1c show subject specific fitted trajectories using BLUPs of the random intercepts and slopes. Here the model captures both that individuals have different initial trust levels, as well as different trajectories over time.



(a) Fixed effect model $y_{tij} = \beta_1 t + e_{tij}$

(b) Random intercept: $y_{tij} = \beta_1 t + v_{0ij} + e_{tij}$

(c) Random intercept & slope: $y_{tij} = \beta_1 t + v_{0ij} + v_{1ij} t + e_{tij}$

Figure 2.1: Fitted trajectories from three multilevel specifications applied to the same repeated-measures data on team trust (three individuals shown). Lines are (subject specific) fitted trajectories $\widehat{y}_{tij}$. The panels contrast how different multilevel specifications allow for different trajectories across individuals.

While multilevel models provide a flexible framework for capturing average trends and differences in individual or group trajectories, they assume that the variability around these effects is constant. In practice, however, the amount of variability may itself depend on individual or group characteristics, or change over time. To address this, we turn to *location–scale models*, which explicitly model such heterogeneity in variances.

2.2 Location-Scale Models

While multilevel models address dependencies, they assume constant variability across groups, individuals, or time. Yet in team research, variability itself can be substantively meaningful. The classic multilevel model (2.1) assumes that the variability around group and individual effects is constant, that is, homoscedastic error terms and random effects. In practice, however, this assumption is often too restrictive: the amount of variability can itself differ between groups, between individuals, or across time. For example, some groups may be more homogeneous than others, or some individuals may show more fluctuation in their responses than others.

Location–scale models (e.g. Cleveland et al. (2002), Foulley and Quaas (1995), and Lee and Nelder (2006)), also called heterogeneous variance models, address this by introducing separate submodels for the variances, known as scale models. Instead of assuming constant variances, the distributional assumptions in the multilevel model (2.1) are replaced with:

$$
\begin{aligned}
\tau_j &\sim N\left(0, \sigma^2_{\tau_j}\right),\ \sigma^2_{\tau_j} = \exp\left(\mathbf{x}'_j \boldsymbol{\delta}_\tau\right), \\
v_{ij} &\sim N\left(0, \sigma^2_{v_{ij}}\right),\ \sigma^2_{v_{ij}} = \exp\left(\mathbf{x}'_{ij} \boldsymbol{\delta}_v\right), \\
e_{tij} &\sim N\left(0, \sigma^2_{e_{tij}}\right),\ \sigma^2_{e_{tij}} = \exp\left(\mathbf{x}'_{tij} \boldsymbol{\delta}_e\right).
\end{aligned}
\tag{2.2}
$$

Here the variances are allowed to vary across groups, individuals, and/or time points. To ensure positivity, they are modeled as exponential (or equivalently, log-linear) functions of covariates $\mathbf{x}$. These covariates can come from the current level or higher. For instance, the between-individual variance $\sigma^2_{v_{ij}}$ could vary as a function of individual-level characteristics such as gender, or as a function of group-level characteristics such as the group's gender composition. The framework can be extended further by including random effects also in the scale part of the model, e.g.

$$
\sigma^2_{v_{ij}} = \exp\left(\mathbf{x}'_{ij} \boldsymbol{\delta}_v + \omega_j\right), \tag{2.3}
$$

where ω_j captures random group deviations around the expected between-individual variability.

Example. Returning to the study of *team trust*, imagine that individuals differ not only in their average trajectories, but also in how much variability there is around those trajectories. Younger individuals may be more similar to each other in their initial trust, while older individuals may show a wider spread due to more varied past experiences. In this way, the variance itself becomes a quantity of interest, potentially explained by covariates such as age or gender. One could also imagine that the variability in trust increases over time as individuals interpret events differently. Figure 2.2 illustrates how location scale models capture this.

First, consider the case of measurement-level heterogeneity, where the variability of the residuals increases over time. Figure 2.2a shows observations, the model implied mean trajectory and a pointwise 95% predictive interval for a singe observation at time t around it, from the following model:

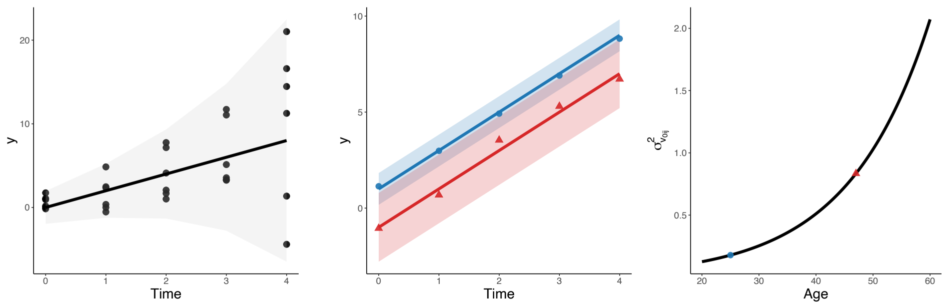
$$
\begin{aligned}
y_{tij} &= \beta_1 t + e_{tij}, \\
e_{tij} &\sim N\left(0, \sigma^2_{e_{tij}}\right), \sigma^2_{e_{tij}} = \exp(\delta_e t).
\end{aligned}
$$

The predictive interval (the shaded area) shows how the variability increases as a function of time.

Next, consider the case where the individual-level variability varies as a function of age. We use the following model:

$$
\begin{aligned}
y_{tij} &= \beta_1 t + v_{0ij} + e_{tij}, \\
e_{tij} &\sim N\left(0, \sigma_e^2\right), \\
v_{0ij} &\sim N\left(0, \sigma_{v_{0ij}}^2\right), \sigma_{v_{0ij}}^2 = \exp\left(\delta_0 + \delta_1(age - \overline{age})\right).
\end{aligned}
$$

Figure 2.2b show individual trajectories for two individuals of different age without noise, i.e. $\beta_1 t + v_{0ij}$, and observations including noise (points). The shaded areas show the dispersion of latent individual means across hypothetical people of that age around the trajectories, excluding measurement noise. Figure 2.2c show the scale model; the variance as a function of age. The points mark the two individuals from Figure 2.2b. The variability for individuals aged 25 (blue) is smaller than the variability for individuals aged 47 (red).



(a) Measurement-level scale: mean trend with pointwise 95% predictive band.

(b) Individual-level scale by age: two individuals' fitted trajectories and between-person variability.

(c) Variability as a function of age; points correspond to the two individuals in (b).

Figure 2.2: Two different scale models for team trust. (a) Measurement-level heteroscedasticity. (b) Individual-level scale by age: two individuals' trajectories. (c) Variability function used in (b), with the same individuals marked.

Location-scale models thus extend multilevel models by allowing heterogeneity in the amount of variability. However, both frameworks still assume linear trajectories of change over time. To capture nonlinear patterns in team trust, for instance, rapid increases early on followed by plateaus, we turn to *Gaussian process models* which provide a flexible way to represent nonlinear trajectories.

2.3 Gaussian Processes

Beyond nested structures and variance heterogeneity, many group processes evolve in nonlinear ways. While multilevel and location-scale models allow for individual and group heterogeneity, they typically assume a predefined, most often linear or polynomial, functional form for the trajectories over time. In many applications, however, this is unrealistic: group processes may accelerate, decelerate, or fluctuate over time, and a more flexible method is required. To model such complex nonlinear patterns, *Gaussian processes* (GPs) can be used.

GPs are a flexible, nonparametric tool used for fitting continuous functions in statistics and machine learning (Rasmussen, 2003; Rasmussen & Williams, 2006; Roberts et al., 2013). The advantage compared to the traditional multilevel and location-scale models is that we need not commit to a functional form in advance, but only need to specify a *mean function*, which describes the average level of the process at each time, and a *covariance (kernel) function*, which controls how strongly values at two different times move together. Hence the GPs are often considered a nonparametric method.

Restricting our treatment to the temporal setting, the function corresponds to a trajectory over time, $f(t)$. The observations at any set finite set of time points are assumed to follow a multivariate Normal distribution. That is, at each time point t, the estimate $f(t)$ is a Normal random variable, and for two time points t and t' the joint distribution of $[f(t), f(t')]$ is bivariate Normal and so on. A Gaussian process is fully specified by its mean function $\mu(t) = \mathbf{E}[f(t)]$ and covariance function $\Sigma(t, t') = \mathbf{C}[f(t), f(t')]$.

Several kernel functions are commonly used in practice (Rasmussen & Williams, 2006). Their basic components are the variance σ^2 and a length-scale parameter, ℓ, that controls how quickly correlations decay with distance. One of the most common kernels is the *squared exponential kernel*:

$$\Sigma(t, t') = \sigma^2 \exp\left(-\frac{(t - t')^2}{2\ell^2}\right). \tag{2.4}$$

It produces very smooth functions with strong correlations for points close in time. To allow for different degrees of smoothness, kernels from the *Matérn family* can be used. The general form is

$$\Sigma(t, t') = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu}\,|t - t'|}{\ell}\right)^{\nu} K_\nu\left(\frac{\sqrt{2\nu}\,|t - t'|}{\ell}\right), \tag{2.5}$$

where $\nu > 0$ controls smoothness, $\Gamma(\cdot)$ is the gamma function, and K_ν is the modified Bessel function. Larger ν yields smoother trajectories; the squared exponential kernel is recovered as $\nu \to \infty$. If $\nu = 1/2$, the *exponential kernel* is obtained, which models correlations that decay exponentially with distance, producing rougher, less smooth sample paths compared to the squared exponential kernel:

$$\Sigma(t,t') = \sigma^2 \exp\left(-\frac{|t-t'|}{\ell}\right). \tag{2.6}$$

The *periodic kernel* can be used to capture recurring patterns, such as cycles or seasonal effects:

$$\Sigma(t,t') = \sigma^2 \exp\left(-\frac{2\sin^2(\pi|t-t'|/p)}{\ell^2}\right). \tag{2.7}$$

Here, p is the period and ℓ controls how quickly correlations decay away from exact multiples of p, so that correlations are strongest for points separated by multiples of the period.

Most standard kernels, as the ones introduced above, yield *stationary* processes where the expected values and variances are assumed to be constant across time, and the covariances depend only on time lag, not the actual values of time (Rasmussen & Williams, 2006; Shumway et al., 2000). However, the kernels can be modified to account for non-stationarity (see e.g. Rasmussen and Williams (2006).

Example. Returning again to the study of *team trust*, suppose that trust does not evolve as a straight line but instead follows nonlinear trajectories where it can grow, plateau, and dip over time. Such nonlinear patterns cannot be captured by a simple random slope. Gaussian processes, however, provide the flexibility to represent these curved and fluctuating trajectories. Figure 2.3 illustrates this idea, showing three individual trajectories (different colors) modeled using a Gaussian process. The data is generated from the following model:

$$\begin{aligned} y_{tij} &= v_{ij}(t) + e_{tij}, \\ e_{tij} &\sim N\left(0, \sigma_e^2\right), \end{aligned}$$

where $v_{ij}(t)$ is a GP with mean function set to zero, and a Matérn kernel with with $\sigma^2 = 1$, $\ell = 3$, and $\nu = 2.4$. The residual variance is $\sigma_e^2 = 0.1$. The GPs follow the individual observations (points) in a more flexible way than the previously discussed models.

Gaussian processes thus extend the multilevel framework by moving beyond linearity, providing a powerful way to capture nonlinear dynamics in group processes. Yet many research questions involve not only how a process evolves over time, but also how it relates to discrete events (e.g., when individuals leave a team). To address this, we turn to *joint models*, which combine longitudinal and event-history data in a unified framework.

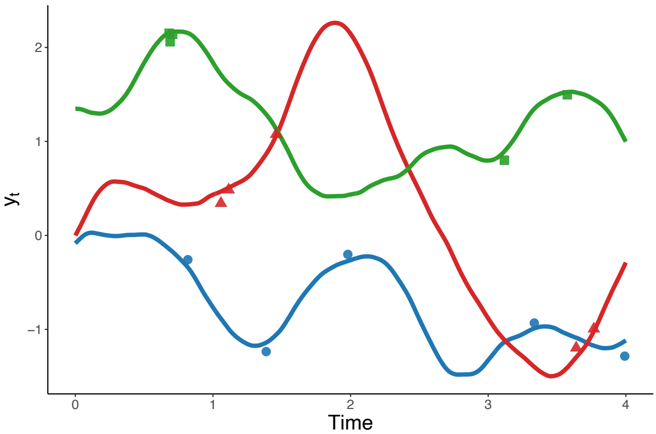


Figure 2.3: Illustration of how Gaussian process models can capture nonlinear trajectories in team trust. Unlike the linear patterns in multilevel or location-scale models, Gaussian processes allow trajectories to bend and fluctuate smoothly over time, reflecting more complex and flexible patterns of change. The parameters are set in the example in the main text.

2.4 Joint Models

So far, we have focused on modeling longitudinal processes such as changes in team trust over time. In many applications, however, researchers are also interested in discrete events, such as when individuals leave a team. The central question is how the longitudinal process is related to the timing of the event. To address this, *joint models* combine a longitudinal model with an event history (or survival) model in a single framework (Asar et al., 2015; R. Henderson et al., 2000). The aim is to quantify the association between the two processes, while appropriately accounting for uncertainty in both.

Let Y_{it} be the longitudinal outcome of individual i at time t, and (T_i, D_i) the event history outcome for the same individual. Here, $T_i = min(\tilde{T}_i, C_i)$ is the observed event time variable, where $\tilde{T}_i$ is the time to event, and C_i the time to censoring (i.e., the exact event time is unobserved). D_i is an event indicator, $D_i = I(T_i = \tilde{T}_i)$ which indicates whether the event happened during the study period.

A basic joint model can then be specified as

$$
\begin{aligned}
Y_{it} &= M_{it} + \epsilon_{it} = X_{it}\beta + Z_{it}v_i + \epsilon_{it}, \\
v_i &\sim N(0, \sigma_v^2), \\
\epsilon_{it} &\sim N(0, \sigma_\epsilon^2), \\
h_i(t) &= h_0(t) \exp\left(W_i\alpha + M_{it}\gamma\right).
\end{aligned}
\tag{2.8}
$$

The longitudinal model is commonly specified as a linear mixed model, i.e. a multilevel model. Here $M_{it} = X_{it}\beta + Z_{it}v_i$ is the linear predictor with fixed effects β and individual-specific random effects v_i, and ϵ_{it} are error terms. Individuals (and thus their random effects) are assumed independent, and errors are assumed mutually independent and independent of the random effects. The model can be generalized to accommodate non-continuous outcomes or multiple longitudinal processes (Rizopoulos, 2012).

The event history submodel models the *hazard*: the moment-to-moment risk that an event happens now, given it hasn't happened yet (e.g., the chance a team member leaves at this instant, among those still on the team). It specifies the hazard of the event of interest as a function of time and the longitudinal process. Here $h_0(t)$ is the baseline hazard, W_i are covariates with fixed effects α, and M_{it} is the linear predictor from the longitudinal model. The parameter γ captures the association between the longitudinal process and the event: in the simplest case, a one-unit increase in the current value of the longitudinal process corresponds to a γ-fold change in the hazard of the event. Other association structures are the current slope, where the slope of the longitudinal trajectory at a specific point in time is associated with the hazard, and the cumulative association, where the accumulated information about the longitudinal process up until the specific time point is used to explain the hazard rate. (see Rizopoulos, 2012, Section 5.1)

As in traditional survival analysis, we assume *non-informative censoring* (Aalen et al., 2008; Rizopoulos, 2012), meaning that the censoring time is independent of the risk of experiencing the event. A further key requirement is the *conditional independence assumption*: given the random effects, longitudinal outcomes are independent of each other and of the time-to-event outcome. These assumptions make it possible to factorize the joint likelihood into separate parts for the submodels.

Example. Consider the association between *team trust* and the decision to leave the team. Joint models may capture this phenomenon by simultaneously estimating the trajectory of trust and the risk of leaving the team, thereby quantifying how the trust influences the hazard of leaving. Figure 2.4 illustrate a longitudinal trajectory of trust, and how different association structure affect the hazard. The current value association connects the value of trust at a time point to the hazard of leaving at that same timepoint. The current slope association connects the rate of change in trust to the hazard att that time point. This is suitable if we believe that rapid changes in trust influence the risk of leaving more than than the actual value of trust. Finally, we have the cumulative association structure, suitable if we believe that the full history of an individuals team trust can explain the hazard of leaving the team.

Joint models thus extend the multilevel framework by linking longitudinal processes with discrete events. This allows researchers to address substantive questions

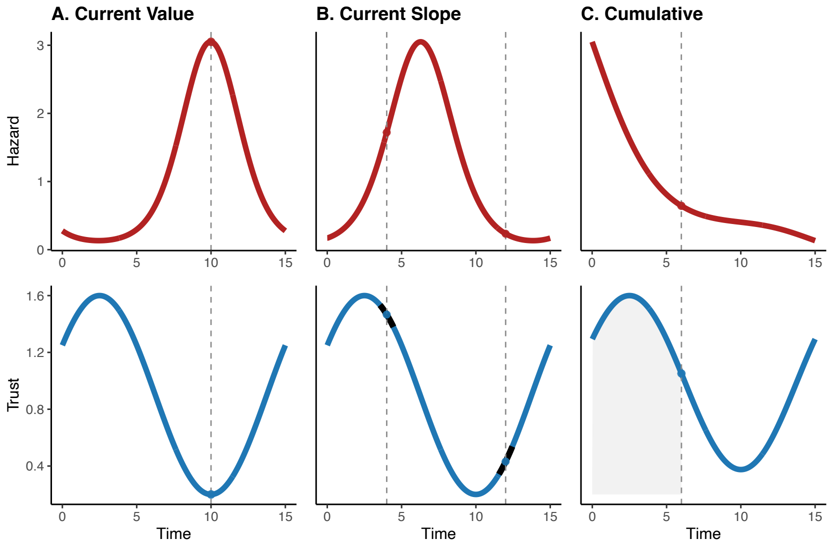


Figure 2.4: Joint model associations between team trust and the hazard of leaving the team. Bottom row shows an example trust trajectory $m(t)$; top row shows the corresponding hazard $\lambda(t)$ under three association structures: (A) current value, $\lambda(t) = h_0(t)\exp\{\gamma\, m(t)\}$; (B) current slope, $\lambda(t) = h_0(t)\exp\{\gamma\, m'(t)\}$ (black segments mark local slope windows); and (C) cumulative (area), $\lambda(t) = h_0(t)\exp\{\gamma \int_0^t m(u)\, du\}$ (shaded area indicates the cumulative exposure). Vertical dashed lines align the evaluation times across panels. Here $\gamma < 0$, so higher trust implies lower hazard.

about how within-team dynamics (such as trust) relate to major transitions (such as leaving the team). A further complication in empirical research, however, is that longitudinal data are often incomplete. In the next section we therefore turn to the problem of *missing data*.

2.5 Non-Ignorable Missing Data

In empirical research, missing data are almost inevitable, particularly in longitudinal team studies where participant fatigue, attrition, and dropout are common (Kozlowski & Chao, 2018). Rubin's (1976) taxonomy distinguishes between three types of missingness: *Missing Completely at Random* (MCAR), where the probability of missingness is unrelated to either observed or unobserved data; *Missing at Random* (MAR), where missingness may depend on observed but not unobserved data; and *Missing Not at Random* (MNAR), where the probability of missingness can depend, in addition to the observed data, on the unobserved values themselves.

When no data are missing, inference is based on the full-data model

$$p(\mathbf{y} \mid \mathbf{x}, \theta), \tag{2.9}$$

where $\mathbf{y}$ is the observed response vector, $\mathbf{x}$ the observed covariates, and θ the parameters of interest. With incomplete data, the setup must also account for the missing observations $\mathbf{y}_{\text{mis}}$ and missingness indicators $\mathbf{r}$. Let $\mathbf{Y} = (\mathbf{Y}_{\text{obs}}, \mathbf{Y}_{\text{mis}})$ denote the complete responses and $\mathbf{R}$ are missingness indicators, with 1 indicating that Y is observed and 0 that Y is unobserved. The full-data model can then be factorized as

$$\begin{aligned} p(\mathbf{y}_{obs} \mid \mathbf{x}, \omega) &= \int\limits_{\mathbf{y}_{mis}} \int\limits_{\mathbf{r}} p(\mathbf{y}_{obs}, \mathbf{y}_{mis}, \mathbf{r} \mid \mathbf{x}, \omega)\, d\mathbf{r}\, d\mathbf{y}_{mis} \\ &= \int\limits_{\mathbf{y}_{mis}} \int\limits_{\mathbf{r}} p(\mathbf{y}_{obs}, \mathbf{y}_{mis} \mid \mathbf{x}, \theta)\, p(\mathbf{r} \mid \mathbf{y}_{obs}, \mathbf{y}_{mis}, \mathbf{x}, \psi)\, d\mathbf{r}\, d\mathbf{y}_{mis} \end{aligned} \tag{2.10}$$

with $\omega = (\theta, \psi)$. Under MCAR, or MAR and some additional assumptions to ensure ignorability (Daniels & Hogan, 2008), inference may proceed using only the observed-data likelihood based on $p(\mathbf{y} \mid \mathbf{x}, \theta)$. In contrast, under MNAR, the missingness mechanism $p(\mathbf{r} \mid \mathbf{y}, \mathbf{x}, \psi)$ must be modeled explicitly (Daniels & Hogan, 2008; Little & Rubin, 2020). If this mechanism is ignored, estimates can be severely biased.

There are three types of main modeling approaches for MNAR data; selection models, pattern mixture models, and shared parameter models (Daniels & Hogan, 2008). Common for them is that they allow the probability of missingness to depend directly on unobserved values. For this relationship to be possible to identify from observed data, additional assumptions are required. Unfortunately, these assumptions cannot be verified empirically. Consequently, MNAR analyses are necessarily sensitive to modeling choices, and transparency about these assumptions is essential (Daniels & Hogan, 2008; Mason et al., 2012).

In studies of group dynamics, constructs of interest are often latent and measured indirectly through repeated indicators (e.g., team trust). In such cases, *shared-parameter models* provide a natural approach. These models introduce random effects $\mathbf{b}$ that are common to both the outcome and missingness processes:

$$p(\mathbf{y}, \mathbf{r} \mid \mathbf{x}, \omega) = \int p(\mathbf{y}, \mathbf{r}, \mathbf{b} \mid \mathbf{x}, \omega)\, d\mathbf{b}. \tag{2.11}$$

A typical specification links a dropout (event-history) model to the same random effects that drive the longitudinal trajectories. Shared-parameter models are thus a subclass of joint models, where both observed responses and missingness patterns inform the estimation of the latent trajectory.

Example. Consider studying how *team trust* develops over time. If individuals with low trust are more likely to not respond to surveys, the missingness mechanism depends on unobserved outcomes, i.e. an MNAR situation. A shared-parameter model would assume that the same latent factors driving each person's trust trajectory also influence their risk of dropping out, indirectly linking the two processes. Assuming we have made plausible assumptions regarding the missingness mechanism, the model makes it possible to draw inferences about the development of trust despite non-ignorable missingness, and also to learn how the latent trust affects the risk of not answering the survey.

3. Summary of the Papers

Paper I: Empirical Estimation of Consensus Emergence: Progress, Pitfalls, and the Path Forward

The first paper addresses the first perspective outlined in the introduction: *how emergent states come to be*. We focus on the empirical estimation of consensus emergence, a central mechanism through which composition emergent states form. Consensus emergence describes the process by which initially diverse perceptions within a team align into a shared group perspective. Despite its theoretical importance, existing statistical approaches risk producing misleading conclusions. The traditionally used intraclass correlation coefficient (ICC) conflates individual- and group-level variance, and the Consensus Emergence Model (CEM), proposed as an alternative, has been cautioned to risk spurious conclusions.

We argue that debates around these measures conflate distinct statistical problems. To address this, we introduce a formal, model-independent definition of statistical consensus emergence, which we use to clarify three fundamental pitfalls: (1) non-identifiability of the consensus emergence process, (2) inappropriate statistics that conflate sources of variance across levels, and (3) model misspecification. Using derivations and simulations, we show how these pitfalls can bias conclusions and discuss strategies to mitigate them.

Methodologically, this work advances the foundations for studying emergent group phenomena by clarifying what it means to capture consensus emergence in statistical terms. By connecting the theoretical construct of consensus emergence to a proper statistical representation, the paper directly addresses the gap outlined in the introduction between multilevel theory and empirical practice. It also offers guidance for applied researchers aiming to study how team-level states originate from individual perceptions with greater conceptual clarity and statistical rigor.

Paper II: Heterogeneous Variance Models with Gaussian Processes

The second paper extends the discussion to another core challenge highlighted in the introduction: modeling nonlinear dynamics in team processes. A recurring idea in team research is that changes in variability over time can signal meaningful phenomena, such as increasing convergence or divergence within a team. Existing approaches, such as heterogeneous variance models (HVMs) and mixed-effect location–scale models, make it possible to study variability as a construct in its own right. However, these models typically rely on restrictive functional forms, limiting their ability to capture the nonlinear and irregular dynamics that characterize many emergent states.

In this paper, we extend HVMs by incorporating Gaussian Processes (GPs), yielding a flexible framework for modeling heterogeneous variance in continuous time. This integration allows us to represent nonlinear changes in variability across hierarchical levels and to accommodate irregularly spaced measurement occasions, while preserving the ability of HVMs to decompose variance into distinct sources. Through simulations and empirical illustrations, we show that HVMs with GPs offer greater flexibility, improved fit, and allow a deeper understanding of the pattern whereby the variability decreases, compared to traditional HVMs.

Methodologically, the contribution lies in combining variance modeling with nonlinear temporal dynamics, thereby equipping researchers with tools to better study emergent team phenomena as dynamic systems. By addressing the lack of methods that can capture nonlinear and time-dependent processes, this paper provides a path toward better capabilities to empirically test multilevel theories about how emergent states come to be.

Paper III: How Significant Events and Team Trust in New Venture Teams Predict Member's Departure

The third paper turns to the second perspective outlined in the introduction: once an emergent state has formed, how does it evolve over time and relate to important outcomes? We focus on team trust, a central emergent state theorized to be dynamic and consequential for team functioning (Costa et al., 2018). Despite its prominence in theory, most empirical work on trust has relied on cross-sectional data or simple longitudinal designs, leaving little insight into how trust develops, how it is disrupted by events, and how it predicts team members' decisions to stay or leave.

In this study, we investigate the longitudinal dynamics of team trust in the context of new venture teams. We propose a joint modeling framework that unifies two methodological challenges highlighted in the introduction. First, trust evolves dynamically and may change as a function of significant events, and in turn, trust may affect how individuals perceive these events. To model this, we extend the traditional joint model to incorporate trust as a latent variable and model the longitudinal trajectory and its relation with the events. Second, longitudinal team data are often incomplete, with attrition that is likely related to unobserved trust levels; we address this by modeling missingness as Missing Not at Random (MNAR) using a shared-parameter model. The joint model thus combines a latent longitudinal process for trust with a survival model for member departure, and a shared parameter model for missing data, allowing us to estimate how both how trust changes over time and as a function of events, and how trust relates to the hazard of leaving the team while accounting for missing data.

Substantively, the findings illustrate how significant events shape trust trajectories and, in turn, how trust shapes the perception of events, and how disruptive events act as a mediator between trust and the risk of member exit. Methodologically, the contribution lies in demonstrating how joint models can accommodate longitudinal latent variables common in psychology and organizational behavior, relations between longitudinal trajectories and events, and MNAR missing data within a single framework. This extends the methodological toolbox for studying emergent team states after their formation, aligning statistical models with the temporal and multilevel complexity of team dynamics emphasized in the introduction. In doing so, the paper illustrates how advancing statistical methods makes it possible to empirically examine theoretical propositions about the evolution and consequences of emergent states in teams.

4. Conclusions and Outlook

This dissertation has been motivated by a central gap in the study of team dynamics: while theory emphasizes that teams are multilevel, temporal, and nonlinear systems, statistical methods have often lagged behind, treating dynamic constructs as static, relying on simple aggregation, and imposing overly restrictive assumptions that fail to adequately capture the necessary dynamic properties. As a result, key theoretical propositions about how emergent states form, evolve, and influence outcomes remain empirically underexamined.

Across the three papers, we take steps toward closing this gap. First, we clarify the statistical foundations of consensus emergence and highlight pitfalls that arise when inappropriate or misspecified models are used. Second, we extend existing multilevel variance models by incorporating Gaussian Processes, thereby providing a flexible framework for capturing nonlinear temporal dynamics. Third, we demonstrate how joint models can integrate latent variables, dynamic longitudinal processes, significant events, and non-ignorable missing data, enabling the study of how emergent states evolve over time and relate to important outcomes such as team member departure.

Together, these contributions advance the methodological toolkit for studying emergent phenomena in teams. They show how statistical methods can be adapted to reflect the complexity of team dynamics, separating processes across levels, modeling nonlinear change, and accommodating the realities of longitudinal data. By aligning methods more closely with theory, this dissertation contributes to more rigorous and conceptually faithful empirical research on how teams develop, adapt, and sustain their functioning over time.

4.1 Outlook

While the methodological advances presented in this dissertation address several challenges in studying emergent team phenomena, much remains to be done. Rapid developments in machine learning and the increasing availability of large-scale data sources hold promise for new approaches within team and group dynamics. Equally important is the adaptation of statistical methods that are already well established in other fields but have yet to be applied in group research. The challenge lies in tailoring these tools so that they yield interpretable results and contribute meaningfully to theory development.

Several important questions remain for composition emergence. For instance, models that account for the patterns it can take, such as unequal contributions from members or the role of emerging leaders. There is also a clear need for longitudinal models that identifies theorized stages and transitions between them, for instance in the development of trust from knowledge-based to identification-based forms (Costa et al., 2018). At the same time, compilation emergence remains comparatively underexplored (Eckardt et al., 2021; Kozlowski & Chao, 2018), calling for methods that can capture differentiated, non-additive patterns such as transactive memory systems. Future work should also address reciprocal feedback loops between emergent states and team processes, where constructs such as trust or cohesion may both shape and be shaped by ongoing interactions (Cronin et al., 2011; Marks et al., 2001; Mathieu et al., 2017). Finally, the joint modeling framework is promising for studying team dynamics, and can be developed for more complex structures such as multiple-membership and three-level settings (Tierens et al., 2021), and with richer association structures than the simple current-value specification used here.

Taken together, these avenues underscore that the study of emergent team phenomena remains both theoretically rich and methodologically challenging. Progress will depend on continued efforts to develop models that disentangle complex forms of emergence, capture stage-like transitions, represent reciprocal feedback loops, and accommodate multilevel organizational structures. By advancing such methods, future research can bring statistical practice closer to the temporal, multilevel, and nonlinear complexity of team dynamics, thereby enabling more rigorous tests of the theoretical propositions that motivated this dissertation.

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