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An Empirical Study of Salesforce Control Systems:
An Application of Latent Class and Latent Transition Analysis

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Doctor of Philosophy

Business

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An abstract of
A dissertation submitted to the Faculty of the
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Abstract

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In this dissertation, I seek to understand how the objectives set by managers in a sales organization influence the behavior choices and subsequent performance outcomes of entry-level sales associates. The empirical research is conducted with data provided by the ticket sales division of a professional sports team. Sales-related positions occupy a majority of the workforce in this industry and entry-level sales positions act as a gateway to a front office career in sports. Demographic information is examined with latent class models, and individual-level sales activity records are analyzed using latent class and latent transition models. Parameter estimates from the models represent distinct characteristics of the latent classes and their prevalence in the salesforce. I identify distinct subgroups of high-achievers and low-achievers based on their probability to meet the benchmark level of sales activities set by the management. There is a consistent pattern of high and low achievement divisions throughout the early weeks of the sales training program with little evidence of switching between the latent statuses. Posterior probabilities of latent class membership are informative of the actual training program outcome for the sales associates. With a few weeks of sales activity records, management may detect potential high performers in their early stages of training.

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Introduction

Placed at the frontline of customer interaction, the salesforce constitutes a large proportion of the workforce and serves as an important agent for an organization's financial development. As of May 2023, Sales and Related Occupations account for approximately 9% of the U.S. labor force, contributing to 13.4 million jobs (U.S. Bureau of Labor Statistics 2024). The size of yearly spending on salespeople by firms is above $800 billion in the U.S. (Zoltners et al. 2013). Due to the direct consequence of the salespeople's performance on firm revenue, sophisticated management strategies are designed and catered to a firm's necessities. While it is difficult to measure the proportional outcome that an average employee contributes to a firm, the sales department is unique in that the employees could prove their contribution in terms of sales revenue. Unlike non-sales staff whose earnings are largely salary-based and work hours are fixed, salespeople are often subject to a more flexible contract that is linked to their performance output. A mixture of conditional incentives and rewards could shape the job specifications of the salesforce so that the management can hopefully fulfill its expectations of sales outcomes.

Optimal salesforce compensation schemes serve the purpose of aligning the relatively entrepreneurial operations of the individual salesperson with the organization's sales strategies. The nature of the business in which the firm takes part is reflected in the various tools that are created to stress which goals the salespeople should strive for, to encourage their commitment to a high level of effort, and to maintain their motivation towards expending such effort to fulfill the goals.

Measuring and monitoring the work processes and outcomes is one of those management tools that have recently witnessed rapid changes. One of the consequences of the COVID-19 pandemic was that through the disruption in our private and public life, working remotely have become more widely accepted. At the beginning of the pandemic, managers of organizations that have not invested in measurement and monitoring systems would have found it difficult to oversee the work of their subordinates. Firms would usually have relied on the convenience of being physically present in the same office and keeping an eye on the employees to check their work progress and ensure that enough effort was produced on the job. With remote work environments, an explicit system became necessary to lay out the tasks and predict the amount of time or effort required for its completion, which in turn drove annual or quarterly assessments to a much granular level (Das, Jain, Maheswaran, Slotegraaf, and Srinivasan 2021).

The problem of managing remote work during the pandemic was partly due to the nature of fixed-salary jobs. Theories in salesforce control systems classify such management as behavior-baesd control (Anderson and Oliver 1987). If it is difficult to measure the exact financial contributions of the task in question, a contract of a regular payment in exchange for a list of roles and responsibilities are agreed upon between a firm and its employees. The other distinct control system is outcome-based control. For positions that directly generate revenue for the organization, such as the sales department, goals can be communicated to the employee in dollar amounts or in the number and types of deals that are expected within a given time frame. Additional incentives for such professionals can be tied to the result of their sales effort and management can provide commensurate rewards.

Empirical research on disaggregated salesperson behavior has been scarce partly due to the proprietary nature of the data. As the modern work environment incorporates more automated measurements of employee behavior and actions, it is imperative that the connection of behavioral inputs with subsequent financial outputs be analyzed with care. In this dissertation, I focus on the individual salesperson's pattern of behavior that is latent in nature and examine the characteristics of the latent groups that exist within the organization.

The purpose of this dissertation is to understand how newly hired salespeople adapt their behavior to the suggested benchmark through training, and how financial incentives assist or discourage behavior-based management. When individuals are at different levels of work progress and within varying degrees of competitiveness, decision tools can help management plan recruitment schedules and optimize team composition. The context of this empirical study introduces a salesforce management framework where sales activities, as integrated on-the-job training, are monitored and compose a part of the compensation scheme.

I analyze the actions of entry-level sales personnel to identify their commonalities and differences within the sales team. I attempt to draw a picture of what constitutes a potentially successful sales executive and how management can detect talent early in the training process. The latent class model applied to the data arranges individuals in discrete groups and the latent transition model further examines the movement from one latent status to another in subsequent time periods. The resulting conclusion provides an insight into the training and development process of a new employee for sales managers.

This dissertation aims to answer the following research questions:

How does the level of sales activity vary among the salesforce?

Does such classification of sales activity levels evolve over time?

Do behavior-based and outcome-based management tools impact sales activity levels?

> Can we predict the outcome of a salesforce training program with early behavioral trajectory?

The rest of the dissertation is as follows. First, I examine the existing literature on salesforce management and sales activity measurement. Next, I introduce the background of the empirical data and its sales management context. I then present a summary of the latent class and latent transition analysis methods. I interpret the result of the analysis and share the concluding remarks.

Chapter 1

Salesforce Management Literature Review

I first review the literature that discusses different types of salesforce management systems employed at the firm level, followed by an examination of the empirical research conducted on the level of individual salespeople. The chapter concludes with relevant findings in salesforce training and presents the opportunity to further investigate the detailed behaviors of entry-level salespeople.

Types of salesforce control systems

The salesforce control system literature positions the sales government structure of an organization on a continuum of input-based behavior control on one extreme and output-based outcome control on the other extreme (Anderson and Oliver 1987). A fully outcome-driven system compensates its salesforce on the objective measure of one's final sales performance, an example being 100% commission-based earnings. Under the outcome-based control system, the risk – which includes fluctuations in the market economy – is shifted from the firm to the individual salesperson along with the autonomy of employing any means to generate the outcome. The opposite case is a fully behavior-driven system where salespeople receive subjective feedback over the stages of their input process (e.g., selling activities and personal qualities) while being compensated with a fixed salary. Unlike the outcome-based control system, here the salesperson is protected from bearing the risk that is outside of their control. Oliver and Anderson (1994) found in a survey of over 300 firms that, among others, the relative degree of behavior-based control in an organization is correlated with more risk aversion, less extrinsic motivation, and more organizational commitment from their salespeople.

Organizations usually adopt a balanced approach of the two control systems when they manage their salesforce. Contingent upon the nature of the product or service that is being sold and the type of customer relationship that the firm is invested in, the selling task may involve a lot of traveling outside the office which makes it difficult for a manager to closely supervise the selling action. Depending on the organization's software infrastructure, not only the availability but the reliability of sales behavior data may rely on whether the activities are recorded automatically, making it difficult to falsify data by self-reporting. The circumstances lead to a compromised mixture of outcome-based variable pay and behavior-based fixed pay.

The types of control measures deployed by managers have been found to interact with salesperson's regulatory focus and impact selling behavior in highly competitive environments (Miao, Zheng, Zang, Grisaffe, and Evans 2022). A salesperson's tendency to be promotion-focused (prevention-focused) is emphasized under a behavior-based (outcome-based) control by the management. Katsikeas, Auh, Spyropoulou, and Menguc (2018) have found that both outcome control and behavior control measures lead to more exploitative learning under a prevention-focused environment. How a salesperson perceives the strength of the link between effort and resulting performance relies on how they attribute the causes to the internal/external and stable/unstable factors (Teas and McElroy 1986). Attribution of one's sales performance to effort or talent is not only of interest to the managers but also to consumers and their perceptions of service employee relationships (Leung, Kim, and Tse 2020).

Elements of salesforce compensation schemes

The incentive and reward structures designed by sales management vary in their details with the organization's approach to sales. Below I present four categories of salesforce compensation scheme designs that are examined in the marketing literature.

- Individual-based vs. team-based incentives

A sales strategy based on geographic territories may lead to a compensation scheme where the management rewards one regional sales team over another. Such group-based incentives often accompany a sales contest or competition, and devising the optimal competition structure becomes of interest for the managers. Lab experiments have examined the consequences of enforcing rules that determine group-based commissions by maximum or average member performance (Chen and Chung 2021), the effects of group composition on within-group competition (Chen and Lim 2017), and the impact of group or individual incentives on effort levels (Lim and Chen 2014). An ideal group-based incentive would ensure high total sales with minimum free riding among team members. Incentives that reward individual performance may come in the form of conditional bonuses or higher commissions, which are helpful in growing a salesperson's own sales potential.

- Fixed vs. moving goals

Sales managers monitor the salespeople's behaviors and(or) outcomes and provide feedback based on the gap between the expected level of sales performance and the actual performance. Goals are introduced not only to inform the level of acceptable accomplishment for the salespeople, but to motivate one towards expending the optimal amount of effort. Interim sales goals can be used to guide a salesperson's achievement trajectory and their final performance outcome (Patil and Syam 2018). Establishing goals that are challenging enough yet not discouraging can be a demanding task for the management.

Hiking up sales targets over time can be unmotivating to the salesforce, yet too easy targets can dampen the best efforts from high achievers. Jerath and Long (2020) classified salesperson effort exertion patterns into four types. When a salesperson delays their fulfillment of the sales quota by initially expending low effort but then increases their effort near the deadline, their performance is in the shape of a “Hockey Stick”. The salesperson may be seen to be “Giving Up” if their initial high effort does not lead to high performance due to low demand, and they expend low effort for the remaining period as there is no chance to meet the goal. “Resting on Laurels” is described as the pattern where the salesperson’s initial high effort meets high demand, thus quickly closing the gap towards the quota and being less productive near the deadline.

Misra and Nair (2011) examine the “ratcheting” policy of updating sales quotas based on the salesperson’s past performance to better match the goal to the individual’s performance potential. A moving goal can also be determined by the salesperson, where the autonomy to select one’s own goal and reward level is given to the individual (Bommaraju and Hohenburg 2018), or when the pricing decision is delegated to the salesperson from the manager (Lim and Ham 2014).

- Competitions and performance disclosures

A competitive environment may be formed if another salesperson’s performance or ranking information is shared on dashboards (Ahearne, Pourmasoudi, Atefi, and Lam 2024). Such information may acknowledge a person’s relative level of performance without disclosing the identity of the individual. Hossain, Shi, and Waiser (2019) found that knowing one’s own rank and the rank of a peer through public disclosure of sales contest results impact one's own utility and shames low performers.

- Monetary vs. non-monetary rewards

A reward that is beyond monetary may impact extrinsic and intrinsic motivation for salespeople (Good, Hughes, and Wang 2022). When incentives are solely cash-based and do not include non-cash based merchandise, it may lead to lower sales performance and effort (Viswanathan, Li, John, and Narasimhan 2019).

A compensation scheme may also include disincentives that take away rewards or result in the loss of a job. In a field experiment, Chung and Narayandas (2017) applied punitive incentive measures that resulted in an insignificant, but a directionally positive effect on sales performance. Boichuk, Bommarju, Ahearne, Kraus, and Steenburgh (2019) have found that a firm that threatened low performers with termination noticed a large improvement in sales performance, specifically when the threat held credibility with replacement trainees who were ready to fill the spot.

Empirical studies on sales effort and performance

Based on their working conditions and the types of customers they work with, sales representatives can engage in outside selling, inside selling, or a hybrid of the two (Shi, Sridhar, and Grewal 2023). In the case of outside sales representatives who interact with customers in-person, the day-to-day activities involved in the selling effort are not readily visible to the management. Thus, sales output was used as a proxy for sales effort to replace the salesperson input that has been difficult to measure and monitor. In Viswanathan, Li, John, and Narasimhan

(2019), sales were observed as a function of ability (fixed effect) and effort. Recent studies have started to include a limited number of sales activity measures to approximate the level of effort spent by outside salespeople. Chung, Kim, and Park (2018) represent sales effort with the number of monthly detailing visits to physicians by pharmaceutical sales representatives. Rao, Viswanathan, John, and Kishore (2021) also examined incentives for pharmaceutical industry salespeople and supervisors that were based on sales activity (monthly visits).

The sources of empirical data on salesperson performance have been concentrated on the pharmaceutical industry (e.g., Katsikeas, Auh, Spyropoulou, and Menguc 2018; Daljord, Misra, and Nair 2016; Misra and Nair 2011), as well as consumer durable goods (e.g., Chung and Narayandas 2017), money lending (e.g., Kim, Sudhir, and Uetake 2022), and military recruitment (e.g., Gatignon and Hanssens 1987). Industries in which customer relationship management is a key feature of a salesperson's responsibilities have adopted compensation schemes that would incorporate the value of the customer. Kumar, Sunder, and Leone (2014) adopted a salesperson value metric by aggregating customer lifetime value at the salesperson level. Kim, Sudhir, Uetake, and Canales (2019) examined compensation schemes that were further divided into customer acquisition and retention bonuses in microfinance bank loans. Salespeople, or loan officers, would be characterized into Hunter or Farmer types who shaped their behavior in response to multidimensional incentives that balance the immediate benefits of new customer acquisition and future benefits of existing customer maintenance (Kim, Sudhir, and Uetake 2022).

Many existing studies are centered on salespeople's reactions toward compensation designs that only reward the sales outcome. While recent research adopts a more comprehensive approach that considers actual measures of salesperson behavior in addition to sales outcomes, the level of activity still does not constitute as part of the compensation scheme such that salespeople are rewarded for their effort regardless of outcome performance (e.g., Chung, Kim, and Park 2018).

The use of training in salesforce management

Salesforce training has been considered as an additional investment to the compensation scheme or as an alternative to financial incentives in the salesforce management literature (e.g., Kumar, Sunder, and Leone 2014). Training can be a means to introduce novice employees to the organization, imbuing cultural belongingness with guidelines and benchmarks. In Cron's (1984) sales career development framework, the first career stage of Exploration usually relate to an entry-level job where one discovers what is expected of them and how to earn rewards and recognition, dependent on the guidance and training from the management. Even for existing employees, training is a way for managers to communicate more concretely what they expect from the salesperson and update their vision of model behavior for optimal outcome.

Empirical studies on salesforce training have examined the differences between onboarding training programs that are centralized in institutional locations and those that are decentralized with on-site learning from experience (Wiseman, Ahearne, Hall, and Tirunillai 2022). Training that is conducted online is found to have positive spillover effects on the salesperson's peers (Singh, Sen, and Borle 2022), and training that was organized for only some part of the salesforce had post-training spillover effects on untrained members of the same team (Atefi, Ahearne, Maxham, Donavan, and Carlson 2018). A study by Luo, Qin, Fang, and Qu (2021) compared the adoption of artificial intelligence coaches in salesforce training. Outside stakeholders such as upstream manufacturers can also invest in training for sales managers and their salespeople, and the study by Magnotta, Murtha, and Challagalla (2020) surveyed the relative effort that salespeople exert for the focal manufacturer with a salesperson effort scale measurement.

A firm's investment in training may incur losses in the case of salesperson turnover (Sunder, Kumar, Goreczny, and Maurer 2017). When training and development results in internal motivation and salesforce assimilation, a lasting relationship can be built between the organization and the salesperson. Studies in sales career development have examined the effects of a salesperson's network position within the organization (Bolander, Satornino, Hughes and Ferris 2015) and the drivers of change for sales representatives which include individual characteristics, sales management, and social influence (Salonen, Terho, Bohm, Virtanen, and Rajala 2021). A recent study by Keshavarz, Rouzies, Kramarz, Quelin, and Segalla (2023) followed the career paths of salespeople and sales managers who have moved within the industry or who have been promoted internally.

Contribution

This dissertation introduces a salesforce compensation scheme which considers the intensity of multiple sales activities in addition to sales performance outcomes, a structure that is unique to the salesforce management literature. The organization that provided the dataset is part of the entertainment industry, specifically in professional sports, which is unlike the usual B2B settings in the existing research. The entry-level sales team is organized under a program that monitors multidimensional measures of salesperson activity which represent the level of input. Acting as an on-the-job training for the new sales representatives, the program aligns its behavioral input goals with the expected level of sales activities that would accomplish optimal sales outcomes. By observing individual-level sales activity on a weekly basis, I investigate the nature of sales behavior with discrete latent groups. The trajectory of each latent group's behavioral input and the transition from one latent status to another is analyzed with latent class and latent transition models.

Chapter 2

Empirical Data Overview

Data used in this research comes from an entry-level ticket sales team of a professional sports team. This organization runs a Sales Development Program that hires new recruits to the ticket sales team throughout the year. The sales associates are assigned with the sale of single game tickets and season passes to individual customers over the phone. A regular season for the professional sports league typically spans from October to April, with postseason playoffs and finals extending up to June. Sales calls are made during the professional sports season and in the months that lead to the next season.

The main task for the sales associates is to make outbound phone calls to potential ticket buyers. At times the sales associate follows up on the sales process with in-person appointments (e.g., stadium tour for potential season pass buyers) and post-sales communication. Once a new sales associate joins the program, they usually complete it within approximately one year. The program acts both as a training course that educates the newcomers to the work environment and as a selection procedure to internally promote strong performers to other sales teams within the organization. Sales teams are arranged by type of product and/or customer, and promoted sales associates are advanced to other teams in the department such as the premium suite sales team or the group sales team. According to the executive who oversees the Sales Development Program, sales-related staff comprise approximately 70% of this organization’s positions. 90% of the senior sales executives had initially started their career in this organization through the entry-level training program. In the professional sports industry, it is commonplace to break into a career with an entry-level sales position as a gateway.

The dataset consists of four different parts: 1) the type and amount of sales activities for each sales associate recorded on a weekly level, 2) the amount of ticket sales revenue generated by each sales associate on a weekly level, 3) the background information of each sales associate at the time of recruitment, and 4) the league performance of the professional basketball team during each season on a weekly level.

The sales manager sets a target for each of the sales activities in this entry-level sales team. There are weekly targets for the number of calls that need to be made to potential ticket buyers, targets for the amount of active call hours, targets for the number of face-to-face appointments, targets for the number of follow-up thank you cards sent to the customers, and targets for the number of referrals accrued by the salesperson. These sales associates are seated in a separate section of the office building in the vicinity of each other.

At the end of each week, each sales activity is scored against the target and then a weighted score of the activities is calculated. This overall score ranks the sales associates against each other. Top ranked sales associates are granted access to the following week's incoming call or chat lines from potential ticket buyers. These inbound sales calls or chats are regarded as opportunities for sales leads as they are expected to have a bigger chance of generating actual ticket sales compared to the usual outbound calls administered by the sales associates. Ticket sales revenue is also compiled and ranked at the end of the week, and the top ranked sales associate gains access to inbound sales calls.

Weekly sales activities and sales revenue are recorded automatically. The number of follow-up thank you cards and the number of referrals are self-reported by the sales associate. A leaderboard of each sales associate's activity and revenue is drawn on a whiteboard in the team's office and the numbers are updated throughout the week. The information disclosure allows sales associates to recognize each other's performance in real time. The sales manager also sends out a team email with the past week's results at the beginning of each week, with special recognition for sales associates who achieved the week's top sales revenue or who have passed a significant cumulative revenue milestone.

Demographic information about the sales associates is collected by the sales manager and the team's intern when the sales associate joins the program. Sales associates self-report information about their age, hometown, university and major, participation in organized sports, siblings and family members, the occupation of their parents, and any previous job experience in sales. The information was not readily collected from sales associates who had participated in the training program's earlier years, and additional information was surveyed on previous program participants who are currently in senior sales positions within the organization.

For each sales associate who participated in the training program, the record of their start date and end date are provided in the database. The organization made follow-up contacts with salespeople who were not selected for internal promotion at the end of the program. Their subsequent careers are classified into sales-related positions in the professional sports industry and non-sales positions.

The individual game tickets and season passes are geographically based on the professional sports team's home venue. The 17,000-seat arena is located in the downtown of a large metropolitan area and was ranked in 2021 as one of the Top 5 sports and live entertainment venues in worldwide ticket sales. While the location also serves as a venue for non-sports entertainment such as music concerts, the tickets to these events are not sold by this sales team. The customer demand for the games may rely on the past performance of the professional sports team playing on the court. Records of the focal sports team's wins and losses from previous games were aggregated on a weekly level that corresponds to the weekly sales activities and revenue data sets.

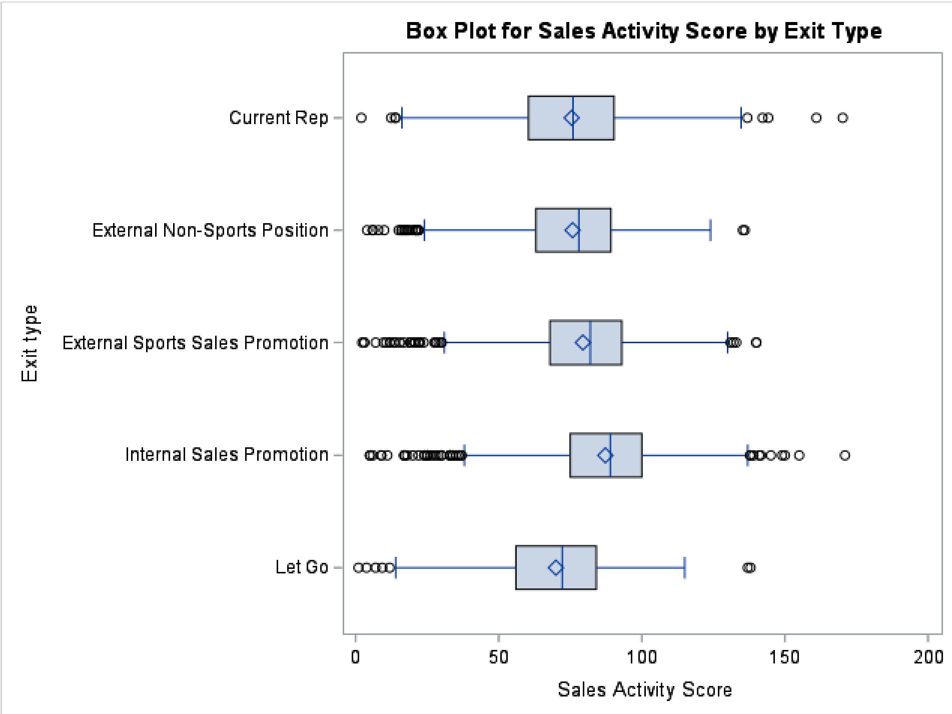
Among the sales associates that had participated in the program in the period between September 2012 and December 2019, I focus on the cohorts that were hired under a consistent compensation scheme between the 2014-15 season and the 2019-20 season. Three to four cohorts of salespeople were hired throughout the year, creating a mixture of more experienced and less experienced sales associates at any given point in time. A new sales associate will initially be surrounded by experienced peers, and over time become one of the most experienced colleagues as they proceed toward the end of the training program. Sales associates with varying degrees of sales experience are competing for the incoming sales leads that are rewarded for highest ranking salespeople in sales activity and sales revenue.

Sales team's compensation scheme design

The sales associates are provided with a base salary and can earn sales commissions that are commensurate to their ticket sales revenue. Their commissions start at 8% of ticket revenue and then increase to 10%, 12%, and 13% when a sales associate reaches three increasing tiers of cumulative sales revenue. While the final commission rate of 13% and its corresponding cumulative sales revenue is presented as the annual target for every team member, not all sales associates finish the program before they reach the target. Some individuals are promoted early or let go involuntarily. Some sales associates may not be internally promoted to positions within the organization despite reaching the annual sales target at the end of the program. The compensation scheme also includes annual contests for sales accrued during the months of February, March, April, and May. Information on the number of sales contest winners and their identity was not available for this study. Monthly sales goals of varying degrees were provided to celebrate high achievers in the last year of the data collection, but the goal amounts or the list of winners were not available for this study.

The following figure illustrates the distribution of overall sales activity scores divided into groups of program outcomes. The overall sales activity score is a weighted sum of individual sales activities that are used in the weekly ranking of sales lead rewards. The sales executives who are terminated early in the training program have the lowest average sales activity score, whereas the internally promoted sales executives have the highest average sales activity score. Individuals who continued their sales careers in the professional sports industry had the second highest average sales activity score, followed by individuals who pursued a non-sports career after the training program.

Figure 1. Distribution of weekly sales activity scores by program outcome



Chapter 3

Latent Class and Latent Transition Models

The interest in classifying latent groups in marketing had been mainly focused on customer relationship dynamics, including studies on brand choice patterns and research on acquisition and attrition patterns of customers. State-dependent and hidden Markov models have been used to identify latent statuses and their changing patterns in alumni gift-giving behavior (Netzer, Lattin, and Srinivasan 2008), physicians' prescription behavior (Montoya, Netzer, and Jedidi 2010), subscription commitment to membership-only services (Ascarza and Hardie 2013), organic food product purchases at supermarkets (Juhl, Fenger, and Thøgersen 2017), customer responses to marketing emails (Zhang, Kumar, and Cosguner 2017), customer utilization of physical and digital purchase channels (Zhang, Chang, and Neslin 2022) and a range of other contexts covered by longitudinal data.

This dissertation adopts the latent class and latent transition analysis methods that are widely applied in social sciences and public health research that track survey responses or recorded measures of individual behavior over time. By identifying similar patterns of responses or behaviors, researchers have uncovered groups that are distinct, for instance, in their types of adolescent delinquency, patterns of female pubertal development, severity of heavy drinking, and their paths into and out of depression (Collins and Lanza 2010).

I first apply static latent class models to demographic profiles of employees to find characteristics that are related to strong sales performance and positive training program outcome. A separate static latent class model is used to analyze sales activities on a weekly basis, and then a repeated-measures latent class model is fit to examine the longitudinal pattern of benchmark achievement in sales activity. Finally, a latent transition model is applied to the early weeks of the training program to better understand the shift in a rookie salesperson's latent status from one week to another.

Latent class analysis

Salesperson types at the point of recruitment are characterized into latent classes using the on-boarding demographics survey. Latent patterns are also uncovered from salesperson behavior to achieve their weekly sales activity goals. Covariate effects of manager, professional sports season, professional sports team's league performance, sales lead rewards, sales revenue, and commission tier are examined.

A static latent class model fits latent categories of salesperson and sales behavior types at a single point in time. The SAS application PROC LCA and its related macros were used to fit latent class models for latent categories of salesperson types at the point of recruitment. Latent class models for latent categories of sales activity patterns were separately applied to weeks 4 through 11.

An individual salesperson i's likelihood contribution can be expressed as (Lanza et al. 2015):

$$P(\boldsymbol{Y}_i = \boldsymbol{y} | X_i = x, G_i = g) = \sum_{l=1}^{n_c} \gamma_{l|g}(x) \prod_{m=1}^{M} \prod_{k=1}^{r_m} \rho_{mk|l,g}^{I(y_m=k)},$$

where $\boldsymbol{Y}_i = (Y_{i1}, \dots, Y_{iM})$ is the vector of salesperson i's records in M behavior categories, X_i is the value of the covariate for salesperson i, G_i is the group membership of salesperson i, n_c is the number of latent classes, $L_i = 1,2, \dots, n_c$ is the latent class membership of individual i, γ refers to the latent class membership probabilities, M is the number of categories for demographic information or sales activities, $1, \dots, r_m$ are the possible values of Y_{im}, ρ refers to the item-response probabilities conditional on latent class membership, and $I(y = k)$ is an indicator that equals 1 if y equals k and 0 otherwise.

The latent class membership probability γ is a logistic regression model with coefficients β for the covariate X (Lanza et al. 2015):

$$\gamma_l(x) = P(L_i = l | X_i = x) = \frac{exp(\beta_{0l} + x\beta_{1l})}{\sum_{j=1}^{n_c} exp(\beta_{0j} + x\beta_{1j})} = \frac{exp(\beta_{0l} + x\beta_{1l})}{1 + \sum_{j=1}^{n_c - 1} \exp\left(\beta_{0j} + x\beta_{1j}\right)},$$

where $l = 1, \dots, n_c$ and the n_cth latent class is used as the reference class.

In a two latent class model with class 2 used as the reference, an individual with the covariate value x will have the following log odds of membership in class 1 relative to class 2 (Lanza et al. 2015):

$$log\left(\frac{\gamma_1(x)}{\gamma_2(x)}\right) = \beta_{01} + \beta_{11}x$$

Repeated-measures latent class analysis

Repeated-measures latent class models estimate the prevalence of latent groups in longitudinal data by recognizing distinct patterns of change among the individuals. Compared to the static latent class models that are applied to cross-sectional data, repeated-measures latent class models are applied to longitudinal data where the $\boldsymbol{Y}_i$ vector of behavior categories are replaced with a vector of a single behavior over time. Thus, they are extensions of latent class models and are different from latent transition models which also estimate transition probabilities. The SAS application PROC LCA and its related macros were used to apply repeated-measures latent class models on multiple weeks of overall sales activity levels.

Latent transition analysis

The latent transition model estimates the changes in latent status membership from one observation period to the next. Salesperson's weekly achievement of meeting the benchmark sales activity is used as the basis of latent status and transition analysis, with a consecutive 4-week, 8-week, and 12-week examination at the beginning of the training program. The SAS application PROC LTA and its related macros were used to fit latent transition models for week-to-week transitions of overall sales activity levels.

An individual salesperson i's likelihood contribution is (Lanza et al. 2015):

$$P(\boldsymbol{Y}_i = \boldsymbol{y} | X_i = x, G_i = g) = \sum_{s_1=1}^{n_s} \cdots \sum_{s_T=1}^{n_s} \delta_{s_1|g}(x) \tau_{s_2|s_1,g}(x) \prod_{m=1}^{M} \prod_{k=1}^{r_m} \prod_{t=1}^{T} \rho_{mk|s_t,g}^{I(y_m=k)},$$

where $\boldsymbol{Y}_i = (Y_{i11}, Y_{i12,} \dots, Y_{i1M}, Y_{i21}, Y_{i22}, \dots, Y_{i2M}, \dots, Y_{iT1}, Y_{iT2}, \dots, Y_{iTM})$ is the vector of salesperson i's records on M behavior categories over T time periods, X_i is the covariate for salesperson i, G_i is the group membership of salesperson i, n_s is the number of latent statuses, δ refers to the latent status membership probabilities at time 1, τ refers to the probabilities of transitions between latent statuses over two consecutive time periods, ρ refers to the item-response probabilities conditional on latent status membership and time period, and

$I(y = k)$ is an indicator that equals 1 if y equals k and 0 otherwise.

The probability of salesperson i belonging to latent status s at Time 1 given covariate value x and group membership g is a multinomial logistic regression (Lanza et al. 2015):

$$\delta_{s|g}(x) = P(S_{1i} = s|X_i = x, G_i = g) = \frac{exp(\beta_{0s|g} + x\beta_{1s|g})}{1 + \sum_{j=1}^{n_s-1} exp(\beta_{0s|j} + x\beta_{1s|j})},$$

where $s = 1,2, \dots, n_s - 1$ and the n_sth latent class is used as the reference class.

In a two latent transition model with status 2 used as the reference, the log odds of membership in status 1 relative to status 2 for an individual belonging to group 1 with covariate value x is (Lanza et al. 2015):

$$log\left(\frac{\delta_{1|1}(x)}{\delta_{2|1}(x)}\right) = \beta_{01|1} + \beta_{11|1}x$$

The probability of salesperson i’s moving to latent status s_2 given the current membership in status s_1, covariate value x, and group membership g is a multinomial logistic regression (Lanza et al. 2015):

$$\tau_{s_2|s_1,g}(x) = P(S_{2i} = s_2|S_{1i} = s_1, X_i = x, G_i = g) = \frac{exp(\beta_{0s_2|s_1,g} + x\beta_{1s_2|s_1,g})}{1 + \sum_{j=1}^{n_s-1} exp(\beta_{0s_2|s_1,j} + x\beta_{1s_2|s_1,j})}$$

Comparison with similar methods

A variable-oriented approach like the factor analysis emphasizes the relationship between variables that applies to the entire group of people observed in the dataset, whereas a person-oriented approach such as the latent class model is interested in identifying divisions within the observed group that are distinct from one another (Bergman and Magnusson 1997). In the context of salesperson training and selection, this dissertation adopts the person-centric approach of latent class and latent transition analyses to focus on the latent groups than the latent traits themselves. If there exists a subgroup of individuals that have high potential for a sales career in the organization, an early detection of such individuals using latent categories of salesperson types would be beneficial to the management at the point of recruitment and in the beginning weeks of training.

Chapter 4

Results of Analysis

This chapter shares the results of analyzing the survey and employee behavior data provided by the ticket sales team of a professional sports organization. I start with the demographic information that is available at the start of each round of training. In the following subsection, I apply the static latent class model to multiple categories of sales activities in a single week. The repeated-measures latent class model is estimated with a multi-week record of overall sales activity scores. The observation window for the repeated-measures latent class model is widened from four weeks to eight weeks and twelve weeks at the beginning of the sales training program. The final subsection examines the specifics of salesperson behavior changes by breaking down the latent state transition on a week-by-week basis.

Latent class analysis of pre-boarding employee survey

Among salespeople who took part in the training program between 2006 and 2019, 186 individuals provided information about their personal and professional backgrounds at the point in time when they joined the program. Questions included any previous experience in sales positions, whether the state that the professional sports team represents is their home state, whether their university major was in Sports, Business or Communications, whether they had previously participated in organized sports, and family background information such as birth order, number of siblings, and parents' occupations.

A summary of the pre-boarding employee survey (Table 1) shows that one in five sales executives have had experience in sales before joining the training program. Nearly 30% of the salespeople were from the state represented by the professional sports team. The three university majors were ranked in the order of Sports (43.6%), Business (39.5%), and Communication (15.1%) with overlaps across majors, and nearly 70% of them had previously played in organized sports. There were slightly more sales executives who had at least one brother (62.4%) compared to a sister (59.5%). Within their families, more employees responded that they were the youngest (36.9%) than the oldest (29.4%) among their siblings. Approximately 14% of salespeople had a father with a career in sales.

Table 1. Pre-boarding employee questionnaire summary

Survey items	Percent
Previous sales experience	21.93
Local to the state	29.65
Undergraduate Major in Sports	43.60
Undergraduate Major in Business	39.53
Undergraduate Major in Communications	15.12
Participated in organized sports	69.94
Has a brother(s)	62.43
Has a sister(s)	59.54
Is the youngest child	36.99
Is the oldest/only child	29.48
Parent (Father) in sales career	13.61

The number of latent classes for the survey responses was selected by comparing the model fit statistics across a different number of latent classes. I compared the baseline model of one latent class with two latent classes up to six latent classes. The EM algorithm is used to calculate the maximum likelihood, and 100 random starting values are used to prevent parameter estimations from being stuck in local maxima. To improve the stability of parameter estimation and avoid bias towards the boundary values of zero or one, a weak prior of 1 is set for β, γ, and ρ.

Table 2 presents the fit statistics for the latent class models. The two latent class model scored the lowest Bayesian information criterion (BIC) and the five latent class model had the minimum Akaike information criterion (AIC) and adjusted BIC. Comparing the magnitude of the increase in model fit shows that the greatest changes when the number of latent classes is increased from one to two. The two latent class model is also favored over the five latent class model in terms of parsimony.

Table 2. Fit statistics for pre-boarding employee survey latent class model

Number of Latent Classes	Number of Parameters Estimated	AIC	BIC	CAIC	Adjusted BIC	log-likelihood
1	11	634.88	670.37	**681.37**	635.52	-1127.38
2	23	589.06	**663.25**	686.25	590.41	-1092.47
3	35	562.69	675.59	710.59	564.74	-1067.28
4	47	548.95	700.56	747.56	551.69	-1048.41
5	59	**538.97**	729.29	788.29	**542.42**	-1031.42
6	71	540.99	770.02	841.02	545.13	-1020.43

Table 3 denotes the latent class prevalences and item-response probabilities under the two latent class model. The larger of the two classes belongs to 68% of the salespeople who provided the demographic information, with a distinguishing characteristic of often being the youngest sibling in the family. The smaller latent class with a 32% proportion is highly likely to be the oldest sibling in the family. Apart from these two survey items, other items were not characteristic of either latent class.

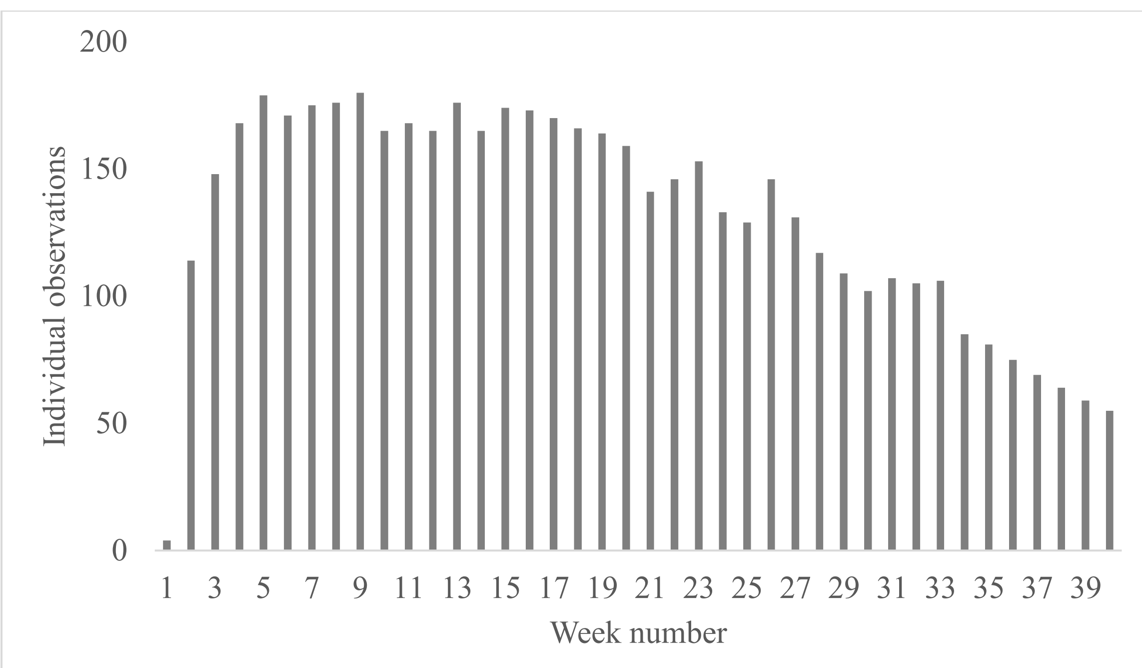
Table 3. Two latent class model parameter estimates (standard errors)

Label	Latent Class A	Latent Class B
Latent class prevalence	0.6809 (0.0507)	0.3191 (0.0507)
Item-response probabilities corresponding to a Yes response		
Have previous sales experience	0.2351 (0.0385)	0.1891 (0.0538)
Georgia local	0.2291 (0.0403)	0.4453 (0.0699)
Majored in Sports	0.4618 (0.0471)	0.3893 (0.0682)
Majored in Business	0.3560 (0.0452)	0.4680 (0.0698)
Majored in Communications	0.1497 (0.0336)	0.1571 (0.0508)
Played in organized sports	0.6840 (0.0436)	0.7269 (0.0621)
Has a brother(s)	0.6118 (0.0457)	0.6442 (0.0672)
Has a sister(s)	0.6072 (0.0463)	0.5809 (0.0699)
Is the youngest sibling	0.5442 (0.0540)	0.0037 (0.0085)
Is the oldest sibling	0.0025 (0.0065)	0.9259 (0.1099)
Father's career in sales	0.1382 (0.0328)	0.1342 (0.0474)

Latent class analysis of weekly sales activity

Each salesperson has unique entry and exit dates into the training program, which creates fluidity in the composition of the sales team members. The length of salesperson tenure, or the number of weeks in the job, varies across individuals. In addition, the sales manager often allows new hires to familiarize themselves to the task for the first few weeks without the pressure of record keeping. This leads to an absence of early sales activity data for many salespeople in the dataset. Figure X portrays the volume of weekly records that are available. The number of recorded sales activities ranged between 165 individuals and 180 individuals between week 4 and week 18. As team members complete their training and exit the program, the number of observations eventually decreases over time. To maximize the data coverage across individuals, the latent class and latent transition analyses will focus on records between week 4 and week 15 of the individual's training period.

Figure 2. Number of individual sales activity records observed per week



To compare the model fit across different numbers of latent classes for the weekly sales activities, I use the week 4 record as a representative. The two latent class model presented the best fit in BIC. The changes in model fit depicted in Table X shows the largest drop in AIC and BIC between one and two latent classes. The three latent class model has the lowest AIC, but for the balance of model parsimony and model fit, I will consider the two latent class model for the following analyses.

Table 4. Fit statistics for week 4 sales activity latent class model

Number of Latent Classes	Number of Parameters Estimated	AIC	BIC	CAIC	Adjusted BIC	log-likelihood
1	6	182.82	200.56	206.56	181.57	-500.56
2	13	79.06	**117.49**	**130.49**	76.36	-441.68
3	20	**66.61**	125.72	145.72	**62.44**	-428.45
4	27	71.99	151.80	178.80	66.37	-424.14
5	34	78.26	178.76	212.76	71.18	-420.27
6	41	87.67	208.86	249.86	79.13	-417.98

The one latent class model describes the average probability of meeting the benchmark for each of the five sales activities that are recorded. Less than half of the team members achieved the benchmark level of sales activity in week 4, except for the activity category Thank You Cards. The two latent class model narrows down the sales activity achievement into two disparate groups. Latent class B, which consists of 68.57% of the group have a higher probability of meeting the benchmark, with an above 50% chance of achieving the benchmark in Outgoing Calls, Call Minutes, Thank You Cards, and Referrals. Latent class A is characterized by a near zero chance of fully meeting the benchmark, with the exception of Thank You Cards.

Table 5. One and two latent class model parameter estimates: week 4

	Meets Benchmark All (100%)	Meets Benchmark Latent Class A (31.33%)	Meets Benchmark Latent Class B (68.57%)
Outgoing calls	0.4225 (0.0415)	0.0111 (0.0239)	0.6103 (0.0531)
Call minutes	0.4014 (0.0411)	0.0060 (0.0133)	0.5818 (0.0537)
Appointments set	0.1408 (0.0292)	0.0029 (0.0106)	0.2038 (0.0413)
Appointments complete	0.3169 (0.0390)	0.0953 (0.0541)	0.4180 (0.0513)
Thank you cards	0.8099 (0.0329)	0.4192 (0.0860)	0.9881 (0.0113)
Referrals	0.3592 (0.0403)	0.0104 (0.0243)	0.5183 (0.0531)

In the following Tables and figures, the comparison between the baseline probability of meeting the sales activity benchmark and the two latent class parameter estimates are repeated for each week from week 5 through week 11. Other than week 9, there is a consistently larger latent group that is more likely to meet the weekly sales activity benchmark level set by the sales manager. Labeled as Latent Class B in each of the separate weeks, the probability of meeting the benchmark is higher than Latent Class A across all sales activities in weeks 4, 5, 6, 7, 10, and 11. Latent Class B is especially outperforming Latent Class A in the areas of outgoing calls and call minutes and presents a higher probability of meeting the Appointments Complete benchmark in most weeks. Latent class categorization in week 8 and week 9 reveal a group with higher chances of meeting the Appointments Complete benchmark despite the low probability of achieving the target levels for number of outgoing calls, call minutes, and appointments set.

Table 6. One and two latent class model parameter estimates: week 5

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All	Latent Class A (23.03%)	Latent Class B (76.97%)
Outgoing calls	0.4610 (0.0420)	0.1499 (0.0913)	0.5540 (0.0522)
Call minutes	0.4113 (0.0414)	0.0122 (0.0271)	0.5307 (0.0565)
Appointments set	0.2128 (0.0345)	0.0408 (0.0490)	0.2642 (0.0448)
Appointments complete	0.4184 (0.0415)	0.1088 (0.0847)	0.5111 (0.0517)
Thank you cards	0.8723 (0.0281)	0.5205 (0.1258)	0.9776 (0.0163)
Referrals	0.4965 (0.0421)	0.0357 (0.0730)	0.6343 (0.0542)

Table 7. One and two latent class model parameter estimates: week 6

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All	Latent Class A (41.36%)	Latent Class B (58.64%)
Outgoing calls	0.4610 (0.0420)	0.0829 (0.0887)	0.7277 (0.0729)
Call minutes	0.4184 (0.0415)	0.0539 (0.0396)	0.6756 (0.0920)
Appointments set	0.1418 (0.0294)	0.0119 (0.0227)	0.2335 (0.0533)
Appointments complete	0.4468 (0.0419)	0.2466 (0.0816)	0.5880 (0.0635)
Thank you cards	0.8582 (0.0294)	0.6902 (0.0794)	0.9767 (0.0209)
Referrals	0.4965 (0.0421)	0.2840 (0.0879)	0.6463 (0.0642)

Table 8. One and two latent class model parameter estimates: week 7

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All	Latent Class A (25.02%)	Latent Class B (74.98%)
Outgoing calls	0.4823 (0.0421)	0.0078 (0.0159)	0.6406 (0.0487)
Call minutes	0.2340 (0.0357)	0.0037 (0.0108)	0.3109 (0.0454)
Appointments set	0.0426 (0.0170)	0.0006 (0.0042)	0.0565 (0.0224)
Appointments complete	0.4610 (0.0420)	0.0400 (0.0355)	0.6015 (0.0491)
Thank you cards	0.7801 (0.0349)	0.1246 (0.0821)	0.9989 (0.0035)
Referrals	0.3972 (0.0412)	0.0062 (0.0139)	0.5276 (0.0499)

Table 9. One and two latent class model parameter estimates: week 8

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (48.99%)	Latent Class B (51.01%)
Outgoing calls	0.4184 (0.0415)	0.0146 (0.0320)	0.8063 (0.1462)
Call minutes	0.3688 (0.0406)	0.0782 (0.1068)	0.6479 (0.0657)
Appointments set	0.1348 (0.0288)	0.1682 (0.0480)	0.1026 (0.0393)
Appointments complete	0.4539 (0.0419)	0.5117 (0.0659)	0.3984 (0.0651)
Thank you cards	0.9787 (0.0122)	0.9567 (0.0257)	0.9998 (0.0016)
Referrals	0.5603 (0.0418)	0.5557 (0.0654)	0.5647 (0.0636)

Table 10. One and two latent class model parameter estimates: week 9

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (62.32%)	Latent Class B (37.68%)
Outgoing calls	0.4786 (0.0422)	0.2437 (0.1449)	0.8670 (0.1511)
Call minutes	0.3357 (0.0399)	0.0743 (0.1001)	0.7681 (0.2581)
Appointments set	0.1714 (0.0319)	0.1415 (0.0421)	0.2209 (0.0731)
Appointments complete	0.5000 (0.0423)	0.5389 (0.0721)	0.4357 (0.0858)
Thank you cards	0.9714 (0.0141)	0.9772 (0.0170)	0.9619 (0.0304)
Referrals	0.6071 (0.0413)	0.5501 (0.0619)	0.7015 (0.0861)

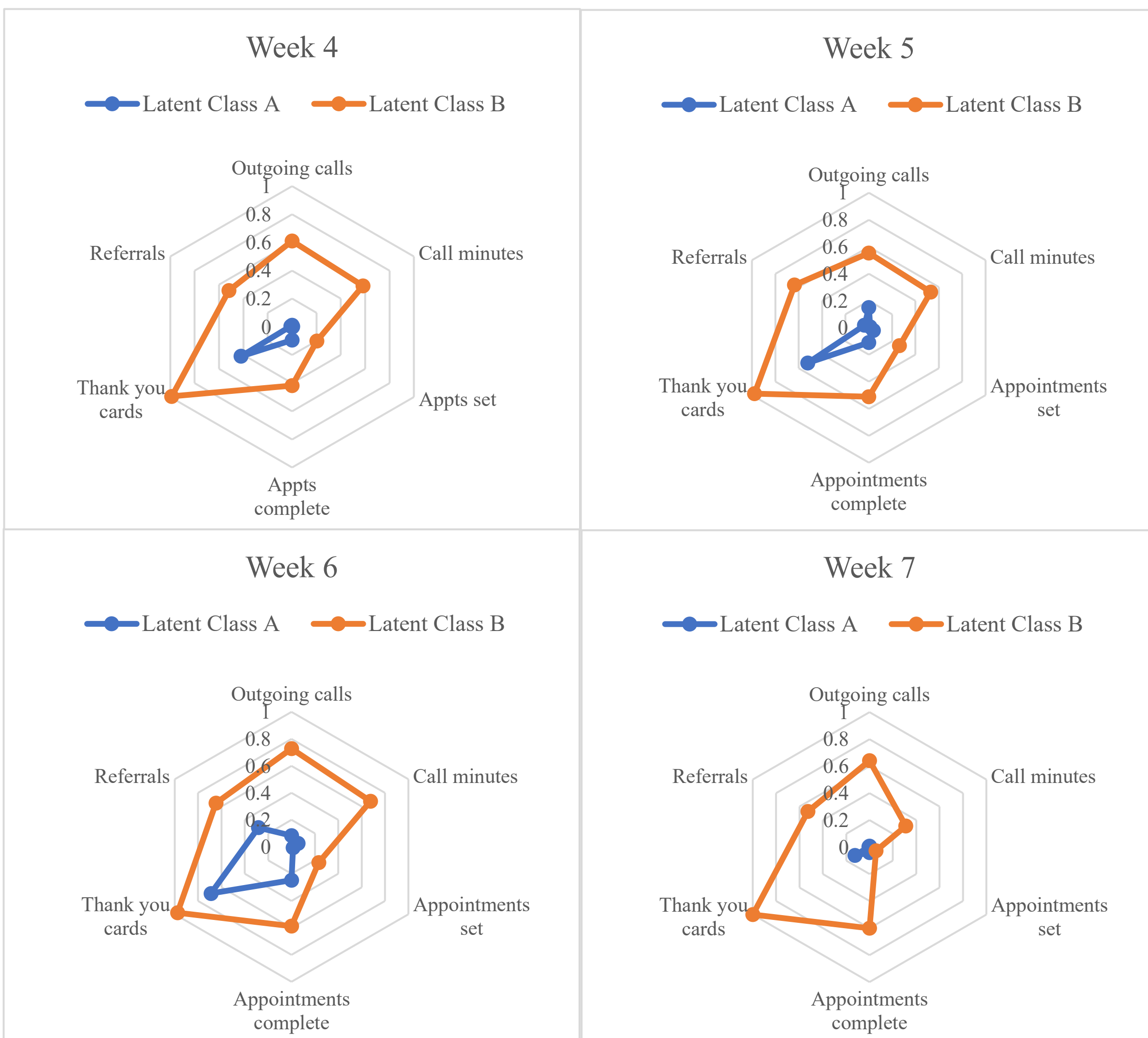
Table 11. One and two latent class model parameter estimates: week 10

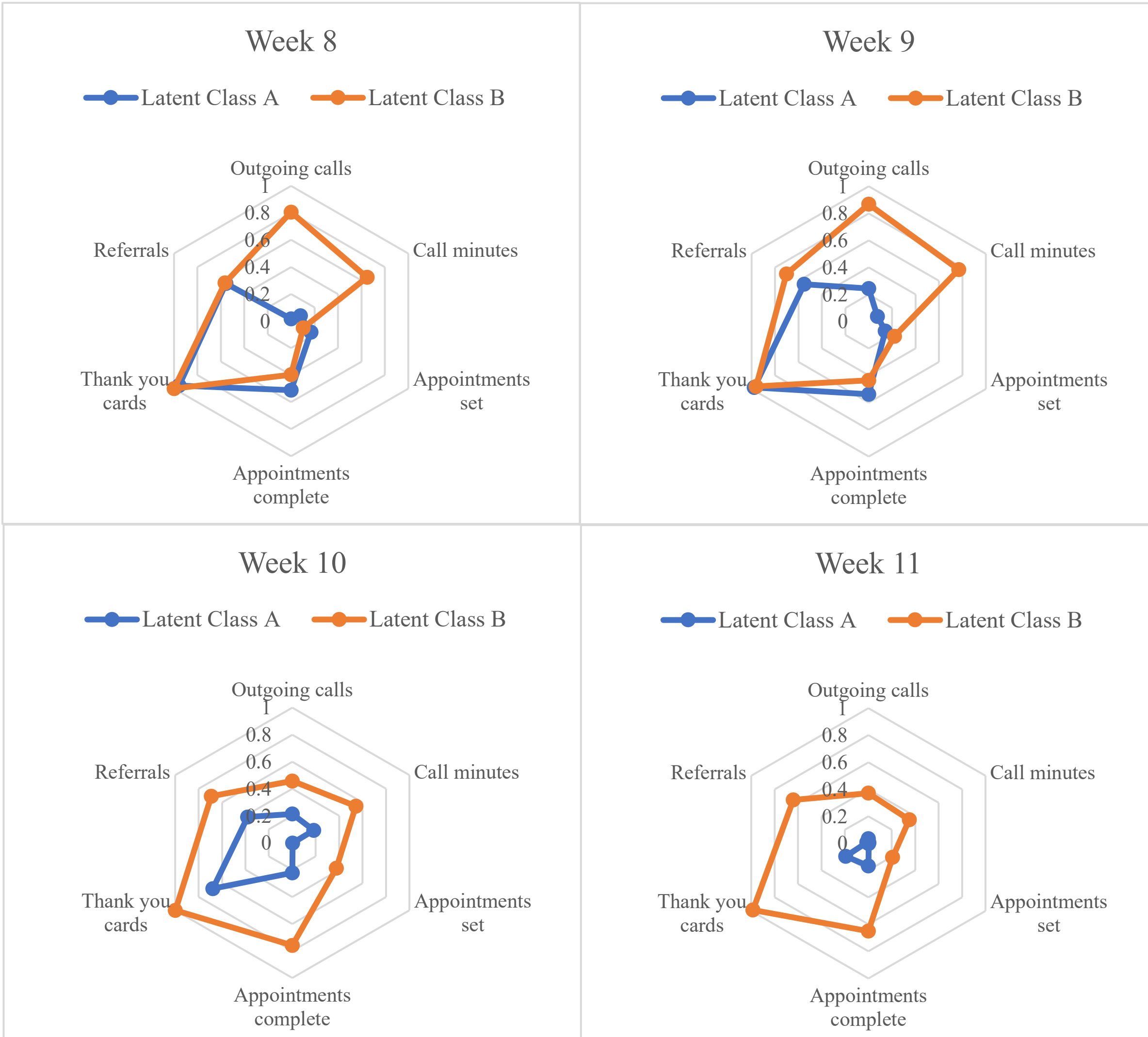
	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (48.88%)	Latent Class B (51.12%)
Outgoing calls	0.3381 (0.0401)	0.2130 (0.0604)	0.4578 (0.0774)
Call minutes	0.3669 (0.0409)	0.1834 (0.0579)	0.5424 (0.0882)
Appointments set	0.1942 (0.0336)	0.0028 (0.0090)	0.3773 (0.0890)
Appointments complete	0.4964 (0.0424)	0.2212 (0.0835)	0.7596 (0.0819)
Thank you cards	0.8417 (0.0310)	0.6782 (0.0832)	0.9981 (0.0067)
Referrals	0.5396 (0.0423)	0.3805 (0.0882)	0.6917 (0.0653)

Table 12. One and two latent class model parameter estimates: week 11

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (20.13%)	Latent Class B (79.87%)
Outgoing calls	0.3030 (0.0400)	0.0348 (0.0497)	0.3706 (0.0491)
Call minutes	0.2803 (0.0391)	0.0068 (0.0182)	0.3492 (0.0489)
Appointments set	0.1667 (0.0324)	0.0037 (0.0127)	0.2078 (0.0405)
Appointments complete	0.5530 (0.0433)	0.1677 (0.1156)	0.6502 (0.0476)
Thank you cards	0.8258 (0.0330)	0.1929 (0.1556)	0.9853 (0.0147)
Referrals	0.5152 (0.0435)	0.0127 (0.0249)	0.6418 (0.0550)

Figure 3. Graphical representation of parameter estimates




Week 8
Latent Class A
Latent Class B
Outgoing calls
Call minutes
Appointments set
Appointments complete
Thank you cards
Referrals
1
0.8
0.6
0.4
0.2
0
Week 9
Latent Class A
Latent Class B
Outgoing calls
Call minutes
Appointments set
Appointments complete
Thank you cards
Referrals
Week 10
Latent Class A
Latent Class B
Outgoing calls
Call minutes
Appointments set
Appointments complete
Thank you cards
Referrals
Week 11
Latent Class A
Latent Class B
Outgoing calls
Call minutes
Appointments set
Appointments complete
Thank you cards
Referrals

Repeated-measures latent class analysis of weekly sales activity

An alternative method of comparing latent classes over time is repeated-measures latent class analysis. In place of the separate sales activities, an overall score for the weekly sales activity is used. An individual has weekly records of whether the overall score met the benchmark. The number of weeks used for the repeated measure latent class model varies among 4 weeks, 8 weeks, and 12 weeks for comparison under different data availability.

Table 13. Fit statistics for repeated-measures latent class model: week 4 to 7

Number of Latent Classes	Number of Parameters Estimated	AIC	BIC	CAIC	Adjusted BIC	log-likelihood
1	4	54.58	66.40	70.40	53.74	-266.11
2	9	**22.23**	**48.83**	**57.83**	**20.36**	-244.93
3	14	29.13	70.52	84.52	26.22	-243.39
4	19	38.52	94.68	113.68	34.56	-243.08
5	24	48.43	119.37	143.37	43.44	-243.03
6	29	58.32	144.04	173.04	52.28	-242.98

Similar to the single week latent class models in the previous subsection, the repeated-measures latent class model using sales activity data from week 4 to week 7 has the best model fit with 2 latent classes. There is an upward trajectory in the probability of meeting the overall sales activity score benchmark for the salesforce as a whole, with one in ten salespeople meeting their overall benchmark in week 4 and the proportion doubling in week 7. The two latent class repeated-measures model reveals consistently increasing probabilities for Latent Class B, with two out of three individuals in this subgroup meeting the overall sales activity score benchmark in week 7.

Table 14. Parameter estimates for repeated-measures latent class model: one latent class and two latent class models, week 4 to 7

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (72.15%)	Latent Class B (27.85%)
Week 4	0.1127 (0.0264)	0.0386 (0.0265)	0.3046 (0.0944)
Week 5	0.1915 (0.0330)	0.0801 (0.0368)	0.4793 (0.1144)
Week 6	0.2128 (0.0343)	0.0806 (0.0389)	0.5543 (0.1229)
Week 7	0.2199 (0.0348)	0.0475 (0.0459)	0.6655 (0.1334)

A repeated-measures latent class model is estimated again using eight weeks of sales activity records between week 4 and week 11. The fit statistics suggest that the two latent class model still has the optimal fit when the longitudinal data is doubled from four weeks to eight weeks. Latent Class B consistently outperforms Latent Class A in its probability of reaching overall sales activity score benchmarks. The sizes of the two latent classes are also similar to the four-week model with Latent Class A being approximately three times the size of Latent Class B.

Table 15. Fit statistics for repeated-measures latent class model: week 4 to 11

Number of Latent Classes	Number of Parameters Estimated	AIC	BIC	CAIC	Adjusted BIC	log-likelihood
1	8	274.86	298.51	306.51	273.19	-539.47
2	17	**185.87**	**236.12**	**253.12**	182.33	-485.98
3	26	185.89	262.74	288.74	**180.47**	-476.99
4	35	191.55	295.00	330.00	184.26	-470.82
5	44	196.91	326.97	370.97	187.75	-464.50
6	53	203.59	360.25	413.25	192.55	-458.84

Table 16. Parameter estimates for repeated-measures latent class model: one latent class and two latent class models, week 4 to 11

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (75.42%)	Latent Class B (24.58%)
Week 4	0.1127 (0.0264)	0.0483 (0.0232)	0.3101 (0.0870)
Week 5	0.1915 (0.0330)	0.0678 (0.0291)	0.5702 (0.1049)
Week 6	0.2128 (0.0343)	0.1078 (0.0336)	0.5340 (0.1038)
Week 7	0.2199 (0.0348)	0.0794 (0.0329)	0.6497 (0.1050)
Week 8	0.1631 (0.0310)	0.1105 (0.0326)	0.3241 (0.0879)
Week 9	0.1929 (0.0332)	0.0580 (0.0286)	0.6022 (0.1055)
Week 10	0.2158 (0.0348)	0.0930 (0.0393)	0.5851 (0.0955)
Week 11	0.2197 (0.0359)	0.1451 (0.0374)	0.4385 (0.1002)

The sales activity records from week 4 to week 15 covers salesperson performance history at four months into the training program. The resulting model fit and parameter estimates are comparable to the four week and eight week models. Within the context of this particular sales team, this suggests that the sales manager may utilize the first two months of performance records to reliably differentiate the two latent classes. While Latent Class B has a higher probability of meeting the overall score benchmark throughout the twelve weeks, the probability itself shows stability and does not continuously increase or decrease over time.

Table 17. Fit statistics for repeated-measures latent class model: week 4 to 15

Number of Latent Classes	Number of Parameters Estimated	AIC	BIC	CAIC	Adjusted BIC	log-likelihood
1	12	596.85	632.32	644.32	594.35	-763.79
2	25	463.35	**537.25**	**562.25**	458.15	-684.04
3	38	458.49	570.81	608.81	450.57	-668.61
4	51	**453.54**	604.28	655.28	442.92	-653.13
5	64	454.56	643.73	707.73	**441.23**	-640.65
6	77	461.93	689.52	766.52	445.89	-631.33

Table 18. Parameter estimates for repeated-measures latent class model: one latent class and two latent class models, week 4 to 15

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (76.24%)	Latent Class B (23.76%)
Week 4	0.1127 (0.0264)	0.0401 (0.0233)	0.3457 (0.0904)
Week 5	0.1915 (0.0330)	0.0854 (0.0338)	0.5313 (0.0973)
Week 6	0.2128 (0.0343)	0.1067 (0.0316)	0.5523 (0.1122)
Week 7	0.2199 (0.0348)	0.1065 (0.0377)	0.5829 (0.0967)
Week 8	0.1631 (0.0310)	0.1203 (0.0327)	0.3001 (0.0862)
Week 9	0.1929 (0.0332)	0.0848 (0.0314)	0.5360 (0.1014)
Week 10	0.2158 (0.0348)	0.1131 (0.0394)	0.5391 (0.0955)
Week 11	0.2197 (0.0359)	0.1284 (0.0352)	0.5005 (0.1100)
Week 12	0.1298 (0.0292)	0.0314 (0.0236)	0.4296 (0.0987)
Week 13	0.2538 (0.0380)	0.1395 (0.0381)	0.5995 (0.1093)
Week 14	0.1538 (0.0315)	0.0639 (0.0264)	0.4257 (0.1084)
Week 15	0.1085 (0.0273)	0.0365 (0.0218)	0.3242 (0.0960)

Covariate effects in repeated-measures latent class analysis

The factors that may impact a salesperson's membership to a particular latent class are incorporated as covariates in the repeated-measures latent class model. I examine the impact of the professional sports season schedule and the sales team management personnel. β parameters are estimated for each covariate in the logistic regression model for latent class membership probability.

Table 19 presents γ and ρ estimates for the latent class membership probabilities and the item-response probabilities for the 12-week repeated-measures latent class model with covariates. The estimates from week 4 to week 15 are consistent with the estimates from the repeated-measures latent class model without covariates in Table 18.

Table 19. Parameter estimates for repeated-measures latent class model with covariates: one latent class and two latent class models, week 4 to 15

	Meets Benchmark	Meets Benchmark	Meets Benchmark
	All (100%)	Latent Class A (79.45%)	Latent Class B (20.55%)
Week 4	0.1127	0.0454 (0.0266)	0.3679 (0.0965)
Week 5	0.1915	0.1054 (0.0339)	0.5159 (0.0996)
Week 6	0.2128	0.1079 (0.0306)	0.6078 (0.1180)
Week 7	0.2199	0.1221 (0.0354)	0.5882 (0.1023)
Week 8	0.1631	0.1236 (0.0331)	0.3118 (0.0912)
Week 9	0.1929	0.0965 (0.0316)	0.5528 (0.1030)
Week 10	0.2158	0.1321 (0.0356)	0.5260 (0.1006)
Week 11	0.2197	0.1306 (0.0345)	0.5433 (0.1115)
Week 12	0.1298	0.0417 (0.0269)	0.4468 (0.1020)
Week 13	0.2538	0.1396 (0.0360)	0.6614 (0.1192)
Week 14	0.1538	0.0559 (0.0240)	0.5033 (0.1173)
Week 15	0.1085	0.0370 (0.0210)	0.3612 (0.1001)

Tables 20 and 21 present the beta parameter estimates and the significance test results for covariates included in the 12-week repeated-measures latent class model. Latent Class B, which has a higher probability of meeting the overall sales activity score benchmark than Latent Class A, is set as the reference class. For salespeople who joined the training program in the 2018-19 season, there is a marginally higher probability of belonging to Latent Class A. The result corresponds to the league performance of the professional sports team. Throughout the observation period, 2019-20 is the season with the least number of wins for the professional sports team, whereas the reference 2014-15 season has the greatest number of wins. A poor performing season for the professional sports team may not only dampen the demand for game tickets but may be inferred to further influence the ticket sales team morale in terms of achieving benchmark level sales activities.

Between Manager 3 and their successor Manager 4, salespeople who joined the training program under Manager 4 are less likely to belong to Latent Class A. Whether the salesperson joins the training program within the professional sports season or outside the season is not a significant factor that impacts one's latent class membership probability.

Table 20. Beta parameter estimates for repeated-measures latent class model with covariates: two latent class model, week 4 to 15

Covariate	Latent Class A	Latent Class B
Intercept	0.1874 (0.8382)	Reference
In-Season	-0.7191 (0.5502)	Reference
2015-16 season	0.1380 (0.9914)	Reference
2016-17 season	1.5590 (1.0052)	Reference
2017-18 season	1.5391 (0.9829)	Reference
2018-19 season	2.1137 (1.1495)	Reference
2019-20 season	2.2052 (1.4130)	Reference
Manager 4	-2.8910 (1.4832)	Reference

Table 21. Beta parameter test (type 3) for repeated-measures latent class model with covariates: two latent class model, week 4 to 15

Covariate	Baseline	Exclusion LL	Change in 2*LL	df	p-value
In-season	Off-season	-678.02	1.68	1	0.1947
2015-16 season		-677.19	0.02	1	0.8804
2016-17 season		-678.25	2.15	1	0.1426
2017-18 season	2014-15 season	-678.08	1.79	1	0.1806
2018-19 season		-678.86	3.35	1	0.0672
2019-20 season		-678.36	2.36	1	0.1248
Manager 4	Manager 3	-679.46	4.56	1	0.0326

As a final step of the repeated-measures latent class analysis, the posterior probabilities of the two latent classes are averaged across groups of actual training program outcomes. As the γ

estimate of latent class membership probability is higher for Latent Class A than Latent Class B, the mean posterior probability for a salesperson to be classified to Latent Class A is also higher than that of B across all outcomes.

The mean posterior probabilities for Latent Class A are higher than the γ estimate of 79.45% except for individuals who were internally promoted. For those sales executives who received an offer to continue working in the organization's sales department, the mean posterior probability for Latent Class B is higher than the γ estimate of 20.55%. In contrast, the sales executives who were fired before completing the training program have a mean average posterior probability of 96.36% for Latent Class A. The notable distinction in these two outcomes allows for an early detection of an individual's potential for success or failure in the program. By analyzing sales activity records from the first early weeks of training, a sales manager could estimate a salesperson's latent class membership.

Table 22. Posterior probabilities against actual outcome at the end of training program

End-of-training Outcome	Mean Posterior Probability for Latent Class A	Mean Posterior Probability for Latent Class B
Current Representative	85.58%	14.42%
External Non-sports Position	85.47%	14.53%
External Sports Sales Position	85.06%	14.94%
Internal Sales Promotion	64.32%	35.68%
Let Go	96.36%	3.64%

A similar analysis can be made by counting the number of individuals with posterior probability above 99%, 95%, and 90% for Latent Class A and Latent Class B. As the latent class prevalence is higher for Latent Class A than Latent Class B, the number of individuals above the cutoff values are also larger for Latent Class A. The training program outcomes are more evenly distributed among individuals above the cutoff values in Latent Class A compared to the counts for Latent Class B. For instance, among the seventeen salespeople who had a 99% or higher posterior probability of being classified to Latent Class B, eleven of them were offered a sales job from the organization and none of them were let go during the training program. The high proportion of internal promotion outcomes are replicated with cut off values at 95% or 90% posterior probability for Latent Class B.

Table 23. Posterior probability ranking against actual outcome at the end of training program

End-of-training Outcome	A 99%	A 95%	A 90%	B 99%	B 95%	B 90%
Current Representative	19	22	26	2	3	3
External Non-sports Position	16	17	17	2	2	2
External Sports Sales Position	18	21	23	2	3	3
Internal Sales Promotion	20	26	28	11	14	15
Current Representative	11	13	13	0	0	0

Latent transition analysis of weekly sales activity

The latent transition model allows for individuals to shift from one latent status to another over consecutive time periods. Sales activity scores against the benchmark values were used for tracking the behavior of the salespeople. Based on the individual salesperson's achievement of the benchmark, the activities were binary coded. Pre-selected starting values were used for parameter estimation to avoid label switching and control the order of the latent statuses.

Table 24 presents the fit statistics for the four-week latent transition model. In the following, I interpret the model with two latent statuses following the BIC as the standard for optimal fit.

Table 24. Fit statistics for latent transition model using weeks 4 to 7

Number of Latent Statuses	Number of Parameters Estimated	G-squared	df	AIC	BIC	log-likelihood
2	22	2202.10	16777196	2240.10	2296.26	-1767.77
3	44	1999.05	16777177	2075.05	**2187.38**	-1666.24
4	72	1934.43	16777152	2060.43	2246.65	-1633.93
5	106	1812.57	16777121	2000.57	2278.41	-1573.00

Table 25 denotes the proportion of individuals in each latent status over weeks 4 to 7. There is a slight fluctuation in the latent status prevalence, but the proportion of Latent Status 1 stays around 20 to 30% of the group and Latent Status 2 stays around 70 to 80%. The transition probabilities portray a sticky process for Latent Status 2, in which there is minimal movement from Latent Status 2 to Latent Status 1. Between week 4 and week 5, there is more transition from Latent Status 1 to Latent Status 2 compared to the changes in week 5 to week 6 or in week 6 to week 7.

Table 25. Status membership probabilities for latent transition model: week 4 to 7

Status	Latent Status 1	Latent Status 2
Week 4	0.3101	0.6899
Week 5	0.1983	0.8017
Week 6	0.2027	0.7973
Week 7	0.3004	0.6996

Table 26. Transition probabilities for latent transition model: weeks 4 to 7

Week 4 to Week 5	To latent status 1	To latent status 2
From latent status 1	0.5872	0.4128
From latent status 2	0.0234	0.9766
Week 5 to Week 6	To latent status 1	To latent status 2
From latent status 1	0.8281	0.1719
From latent status 2	0.0480	0.9520
Week 6 to Week 7	To latent status 1	To latent status 2
From latent status 1	0.7928	0.2072
From latent status 2	0.1752	0.8248

The item-response probabilities of meeting each sales activity benchmark shows a similar pattern to the latent class model, with Latent Status 2 consistently outperforming Latent Status 1 across all activities.

Table 27. Probability of meeting sales activity benchmarks: all weeks

	Meets Benchmark	Meets Benchmark
Sales activity	Latent Status 1	Latent Status 2
Outgoing calls	0.0548	0.5916
Call minutes	0.0100	0.4861
Appointments set	0.0000	0.1797
Appointments complete	0.1035	0.5138
Thank you cards	0.3877	0.9786
Referrals	0.0037	0.5827

The latent transition analysis was repeated after replacing the six sales activity benchmark achievements with a single overall sales activity score used in the repeated-measures latent class model. Tables 29 through 31 present the results. With the compact measure, the reduction in longitudinal data points limits the latent transition model parameter estimation to two latent statuses. Compared to the previous latent transition model, the latent status with a higher probability of achieving the benchmark has less prevalence than the other latent status. The transition probability estimates show that latent statuses derived from the overall sales activity score are highly likely to remain the same over time.

Table 28. Fit statistics for latent transition model using week 4 to 7

Number of Latent Statuses	Number of Parameters Estimated	G-squared	df	AIC	BIC	log-likelihood
2	12	3.59	6	21.59	48.19	-244.61

Table 29. Status membership probabilities for latent transition model: week 4 to 7

Status	Latent Status 1	Latent Status 2
Week 4	0.8728	0.1272
Week 5	0.7571	0.2429
Week 6	0.7056	0.2944
Week 7	0.7056	0.2944

Table 30. Transition probabilities for latent transition model: weeks 4 to 7

Week 4 to Week 5	To latent status 1	To latent status 2
From latent status 1	0.8675	0.1325
From latent status 2	0.0000	1.0000
Week 5 to Week 6	To latent status 1	To latent status 2
From latent status 1	0.8794	0.1296
From latent status 2	0.1919	0.8081
Week 6 to Week 7	To latent status 1	To latent status 2
From latent status 1	0.9999	0.0001
From latent status 2	0.0000	1.0000

Table 31. Probability of meeting overall sales activity benchmark: all weeks

	Meets Benchmark	Meets Benchmark
	Latent Status 1	Latent Status 2
Overall sales activity score	0.0457	0.6226

Covariate Effects in Latent Transition Analysis

I examine the impact of the incoming sales leads on the following week's achievement of sales activity benchmarks. Sales leads are acquired from weekly competition within the ticket sales team for the top weekly sales revenue or the top overall sales activity score. Sales leads are included as covariates for the latent status membership probability δ and for the transition probabilities τ between latent statuses.

The log-likelihood beta test for including the sales lead covariate in the latent status membership probability δ had a p-value of 0.7583 and was not found to be statistically significant. A separate beta test for further including the sales lead covariate in the transition probability τ had a p-value of 0.8876 and was not found to be statistically significant.

Table 32. Beta test for including a covariate in the latent transition model

Covariate	Change in 2*LL	df	p-value
Sales lead (in latent status membership probability)	0.0946	1	0.7583
Sales lead (in transition probability)	6.52	12	0.8876

Conclusion

This dissertation analyzed salesperson behavior and demographic characteristics using latent class and latent transition models. The empirical dataset from a professional sports team's ticket sales division reveal two latent classes (statuses) as the best fitting configuration to interpret their sales activities. The latent classifications are defined by sales activity levels that meet or exceed the benchmarks set by the management. While the probabilities of achieving multiple or overall sales activity benchmarks distinguish the high-achieving latent class from the low-achieving latent class, the patterns of sales behavior from the early weeks of the salesperson training program are found to be consistent over time. In other words, there is a cross-sectional divide within the salesforce in terms of behavior goal achievement, but such classification persists without much fluctuation over time.

The behavior-based incentive provided by management was not significantly related to the transition probability from one latent status to another. A salesperson was more or less likely to belong to a certain latent class depending on which sales manager oversaw the training program and in which professional sports season the training was being held. When the posterior probabilities for the two latent classes were compared with actual career outcomes from the program, the salespeople who received promotions to the organization's sales position were likely to be in a different latent group than those who were let go involuntarily during the program. With little fluctuation in the behavioral patterns of the salespeople, the sales manager would be able to detect a potential internal hire using sales activity data in the early weeks of training.

Data on detailed measurement of salesperson activities have not been easily accessible to previous salesforce management studies, partly due to high overhead costs in monitoring individual behavior. Existing empirical models would use a single sales activity (e.g., number of sales calls) or set sales revenue as a proxy for sales effort. This research examined a variety of activities involved in the selling of professional sports game tickets and classified subgroup characteristics within the salesforce using latent class and latent transition models. There was consistency in high/low achievement of sales activity goals among salespeople included in the dataset.

More sophisticated models for detecting latent groups or patterns could be applicable with a larger sample size to avoid identification problems. Additional information on the selling environment (e.g. seating arrangements) could specify the competition dynamics and learning spill overs among salespeople of varying tenure in the training program. Data on the precise timing of the changes in sales commission tiers would allow for an examination on sharp behavioral changes that follow a permanent monetary reward.

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Appendices

Appendix A. Bootstrap likelihood ratio tests for comparing model fit between k-latent class and (k+1) latent class models (100 bootstrap replications, 20 starting values)

A.1 Salesperson demographics latent class models

Null model	Alternative model	p-value
1-class	2-class	0.01
2-class	3-class	0.01
3-class	4-class	0.02
4-class	5-class	0.01
5-class	6-class	0.70

A.2 Sales activity repeated-measures latent class models (week 4 to week 7)

Null model	Alternative model	p-value
1-class	2-class	0.0099
2-class	3-class	0.7129

A.3 Sales activity repeated-measures latent class models (week 4 to week 11)

Null model	Alternative model	p-value
1-class	2-class	0.0099
2-class	3-class	0.2970

A.4 Sales activity repeated-measures latent class models (week 4 to week 15)

Null model	Alternative model	p-value
1-class	2-class	0.0099
2-class	3-class	0.1188

Appendix B. Test of measurement invariance across groups

B.1 Grouping by manager type (Manager 3 and Manager 4)

	df	G^2
3-class model, no measurement invariance	87	31.14
3-class model, measurement invariance	105	63.14
Change	18	32

Measurement invariance holds with the p-value of 0.0220, larger than 0.01. Interpretation of the three latent classes are identical for each of the managers, and the latent class prevalences can be directly compared across managers.

B.2 Grouping by professional sports season (2014-15, 2015-16, 2016-17, 2017-18, 2018-19, and 2019-20)

	df	G^2
3-class model, no measurement invariance	263	68.63
3-class model, measurement invariance	353	163.63
Change	90	95

Measurement invariance holds with the p-value of 0.3389, larger than 0.01. Interpretations of the three latent classes are identical for each of the seasons, and the latent class prevalences can be directly compared across seasons.

Appendix C. Extended latent transition analysis using 8 weeks of data

With an extended dataset of eight weeks from week 4 to week 11, the latent transition model with two classes had the optimal fit among the models that were measurable. Similar to the four-week model, the latent status transition was sticky throughout the eight weeks of observation.

C.1 Fit statistics

Number of Latent Classes	Number of Parameters Estimated	G-squared	df	AIC	BIC	log-likelihood
2		161.20	238	195.20	245.45	-490.64
3		142.95	208	236.95	375.88	-481.52
4			Not well identified			
5			Not well identified			

C.2 Status membership probabilities for latent transition model with two latent classes: Weeks 4 to 11

Status	Latent Status 1	Latent Status 2
Week 4	0.1168	0.8832
Week 5	0.2253	0.7747
Week 6	0.2341	0.7659
Week 7	0.2341	0.7659
Week 8	0.2623	0.7377
Week 9	0.2623	0.7377
Week 10	0.2914	0.7086
Week 11	0.2950	0.7050

C.3 Transition probabilities for latent transition model with two latent classes: Weeks 4 to 11

Week 4 to Week 5	To latent status 1	To latent status 2
From latent status 1	1.0000	0.0000
From latent status 2	0.1228	0.8772
Week 5 to Week 6	To latent status 1	To latent status 2
From latent status 1	1.0000	0.0000
From latent status 2	0.0114	0.9886
Week 6 to Week 7	To latent status 1	To latent status 2
From latent status 1	1.0000	0.0000
From latent status 2	0.0000	1.0000
Week 7 to Week 8	To latent status 1	To latent status 2
From latent status 1	1.0000	0.0000
From latent status 2	0.0368	0.9632
Week 8 to Week 9	To latent status 1	To latent status 2
From latent status 1	1.0000	0.0000
From latent status 2	0.0000	1.0000
Week 9 to Week 10	To latent status 1	To latent status 2
From latent status 1	1.0000	0.0000
From latent status 2	0.0395	0.9605
Week 10 to Week 11	To latent status 1	To latent status 2
From latent status 1	0.7717	0.2283
From latent status 2	0.0989	0.9011

C.4 Probability of meeting the benchmark: All weeks

	Meets Benchmark	Meets Benchmark
	Latent Status 1	Latent Status 2
Overall sales activity score	0.5562	0.0745