

MILLIMAN REPORT

# Building a long-range GLP-1 forecast: When could commercial health plans see a plateau?

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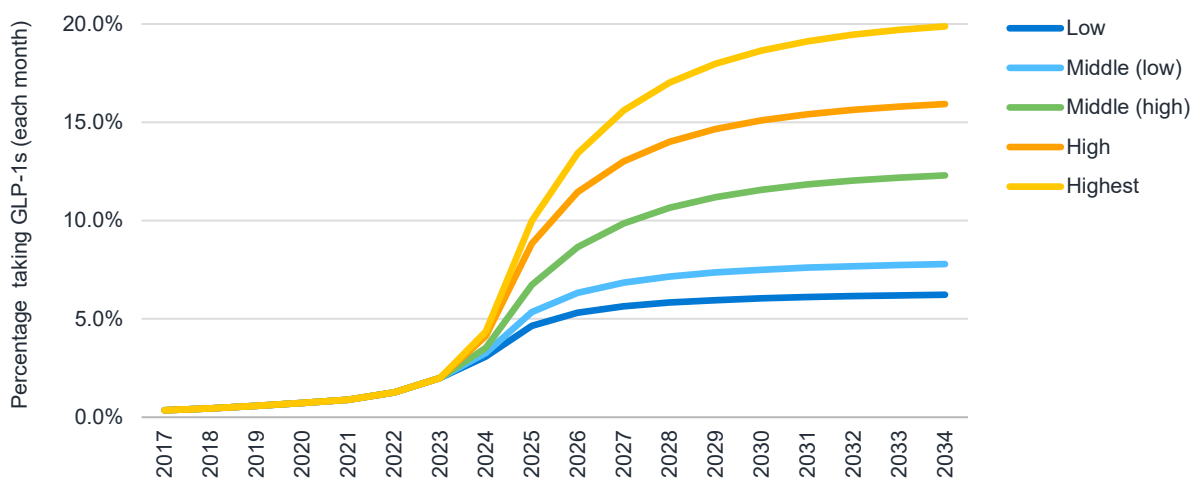
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In recent years, new treatment options for type 2 diabetes and obesity have resulted in substantial changes in clinical guidelines and prescribing patterns. As a result, commercial payers, including self-funded employers, have witnessed a surge in the utilization of glucagon-like-peptide-1 (GLP-1) medications. In addition, this class of medications is being prescribed for an ever-expanding list of approved indications, including sleep apnea and cardiovascular conditions. This white paper provides a framework for building a long-range forecast to help employers covering these drugs understand how trends may change over time.

## Executive summary and key findings

Milliman developed a Markov model to forecast the utilization rates of GLP-1s for a typical population with employer-sponsored health insurance benefits that include coverage of GLP-1s for weight loss.<sup>1</sup> A Markov model is a stochastic modeling technique used to forecast future outcomes based solely on current state information. It uses probabilities of various changes as inputs, making it an ideal approach for modeling processes like weather patterns, speech recognition, user behavior, or in this case, the utilization of a new and emerging therapy. As shown in Figure 1, this model forecasts that utilization trends will continue rising from 2025 to 2027 and then stabilize sometime between 2028 and 2030. Depending on assumptions, the utilization rate is expected to be between 6% and 20%.<sup>2</sup> As long as the mix of GLP-1s and unit costs do not change, increases in utilization will correspond to increases in cost. Users of this white paper are encouraged to review it in its entirety, paying close attention to the Considerations for a long-range forecast section below. This model was generated using historical data, and given the complex interplay of factors that impact GLP-1s, utilization rates and cost trends will continue to evolve.<sup>3</sup>

**FIGURE 1: LONG-RANGE FORECAST (COMMERCIAL POPULATION)**



1. This forecast is valid for a typical employer-sponsored commercial health plan covering these drugs. It is not a reasonable estimate for labor groups, trusts, public employers, and other groups with low cost sharing or atypical demographics, such as early retiree or beneficiaries covered by the Veterans Health Administration (VHA).

2. Those taking GLP-1s each month include all enrollees taking GLP-1s regardless of whether indicated for management of diabetes, chronic weight management, or otherwise. A typical commercial population includes children.

3. Our estimates are based upon the assumptions discussed below and are sensitive toward emerging research, coverage by plan sponsors, formulary strategies, availability through cash pay options, and prescriber practice patterns.

## MODELING ASSUMPTIONS

Our forecast is based upon assumptions derived from real-world data observed in 2024, adjusted to reflect formulary coverage for all groups, assumptions around the increased popularity of these drugs, as well as our expectations of improved persistency for those continuing to use these medications. Because our goal is to understand when GLP-1 utilization may plateau for a group covering GLP-1s for weight loss, we therefore increase the take-up rate for these drugs to reflect full coverage, as well as increased popularity and promotion of GLP-1 therapies.

In our low, middle (low), and middle (high) scenarios, we are implicitly assuming that other therapeutic classes besides GLP-1s may continue to play a prominent role in the treatment of diabetes and chronic weight management. These scenarios also assume that monthly persistency (i.e., continuing to take the drug each month) improves above current levels. Lastly, these scenarios implicitly assume that carriers will continue to manage utilization through prior authorization and that the potential for lower cost sharing will not materially change use of these drugs.

On the other hand, our high and highest scenarios suggest that GLP-1s will become the prominent treatment option for these conditions. This may be driven by reduced cost sharing, increased awareness, and other factors discussed throughout this white paper. These scenarios also assume further improvements in persistency.

FIGURE 2: KEY ASSUMPTIONS BY SCENARIO

| GENERAL ASSUMPTIONS   | LOW    | MIDDLE (LOW) | MIDDLE HIGH) | HIGH   | HIGHEST |
|---|--------|--------------|--------------|--------|---------|
| Estimated percentage of members with coverage for weight-loss GLP-1s in 2024 data                             | 47.7%  | 47.7%        | 47.7%        | 47.7%  | 47.7%   |
| Percentage of members with coverage for weight-loss GLP-1s in forecast (2025+)                                | 100.0% | 100.0%       | 100.0%       | 100.0% | 100.0%  |
| Factor for increased coverage after data year (see Methodology section)                                       | 2.10   | 2.10         | 2.10         | 2.10   | 2.10    |
| Factor to account for increased popularity of GLP-1s, prescribing patterns, and pent-up demand from shortages | 1.25   | 1.25         | 1.25         | 2.50   | 2.50    |
| Total factor for weight-loss GLP-1 take-up (applies to healthy and individuals with history of obesity)       | 2.62   | 2.62         | 2.62         | 5.24   | 5.24    |
| SCENARIO SPECIFIC ADJUSTMENT FACTORS  |        |              |              |        |         |
| Transition to diabetes/obesity  | 0.900  | 1.000        | 1.250        | 1.000  | 1.100   |
| Transition to starting drugs  | 0.900  | 1.000        | 1.100        | 1.000  | 1.100   |
| Transition away from taking drugs   | 1.250  | 1.000        | 0.450        | 1.000  | 0.450   |
| MONTHLY DRUG PERSISTENCY (CONTINUING TO USE GLP-1S EACH MONTH, EXCLUDING ENROLLMENT TERMINATIONS)             |        |              |              |        |         |
| History of diabetes   | 0.965  | 0.972        | 0.987        | 0.997  | 0.999   |
| History of obesity  | 0.929  | 0.943        | 0.972        | 0.973  | 0.987   |
| No history of diabetes or obesity   | 0.937  | 0.945        | 0.963        | 0.976  | 0.985   |

The assumptions in our forecast are informed by the 2025 real-world experience of more than one million commercial lives with full coverage of GLP-1s. This separate database, maintained by Milliman MyRxConsultant, does not contain enrollment data. Therefore, it was not possible to track members and apply this experience to the Markov model discussed later in this white paper.

Our middle (low) and middle (high) scenarios results in 7.9% and 12.7% of the total commercial population using GLP-1s in any given month. Our low and high scenarios result in 6.3% and 16.3%, while our highest scenario results in 20.4%. See the Results section for more details.

FIGURE 3: KEY RESULTS BY SCENARIO

| PROPORTION TAKING GLP-1S IN DISTANT FUTURE | LOW  | MIDDLE (LOW) | MIDDLE HIGH) | HIGH  | HIGHEST |
|--|------|--------------|--------------|-------|---------|
| Percent of total membership taking GLP-1s  | 6.3% | 7.9%         | 12.7%        | 16.3% | 20.4%   |

## Considerations for a long-range forecast

Our forecast is sensitive to a range of external factors, including uncertainties that we may be able to predict and those that are unforeseeable. Our previous experience with the adoption of other new classes of medications, such as second generation antidepressants (i.e., Prozac/fluoxetine), erectile dysfunction medications (i.e., Viagra/sildenafil), disease-modifying antirheumatic drugs (DMARDs) (e.g., Humira and Enbrel), and migraine medications (i.e., Imitrex/sumatriptan) provides a roadmap. Each of these classes were considered blockbuster drugs because they generated significant sales due to a large addressable market and consumer demand. As these drugs launched, their associated costs attracted tremendous attention from plan sponsors. At the time, many plan sponsors had reservations about formulary placement for these medications. Today, these drugs are generally widely available on commercial formularies. If GLP-1 formulary adoption follows the trajectory of other medications after generic versions were launched, we might see near ubiquitous coverage within the next 10–15 years. While our forecast is highly uncertain, we provide key considerations below. Our considerations are organized by whether the future may be influenced by ongoing medical research, providers, health plans and employers, manufacturers, or other factors. In the Methodology section below, we further discuss specific considerations that are adjusted for in the Markov model.

### INFLUENCED BY ONGOING MEDICAL RESEARCH

#### Emerging research and new indications.

Initially, GLP-1s were developed for the treatment of type 2 diabetes. However, over time this class of drugs has gained acceptance in treating an increasing share of the population due to expanded indications, such as chronic weight management. For example, we recognize that GLP-1 medications have recently gained U.S. Food and Drug Administration (FDA) approval to treat conditions such as sleep apnea<sup>4</sup> and cardiovascular disease.<sup>5</sup> Many speculate that these medications may also be used to treat diseases such as alcohol misuse disorder and Parkinson's disease.<sup>6</sup> Further, drug trials are underway to investigate the use of tirzepatide for a weight-related indication for those with comorbid methamphetamine use disorders.<sup>7</sup> Generally speaking, the greater the number of indications for GLP-1s, the more likely those drugs are to be prescribed—both for individuals with a history of diabetes and those without.

#### Introduction of new and newer GLP-1s.

As new GLP-1s are discovered and researched, the potential exists for new variants with less side effects, higher rates of medication adherence, and improved efficacy. The number of individuals taking GLP-1s would generally increase if new and improved GLP-1s are launched.

4. Manalac, T. (December 23, 2024). 7 indications for GLP-1s beyond weight loss. *BioSpace*. Retrieved January 2, 2025, from <https://www.biospace.com/drug-development/7-indications-for-glp-1s-beyond-weight-loss>.

5. Patchen, T. (March 8, 2024). FDA approves drug Wegovy to reduce cardiovascular events. *BioSpace*. Retrieved January 2, 2025, from <https://www.biospace.com/fda-approves-novo-s-obesity-drug-wegovy-to-reduce-cardiovascular-events>.

6. Manalac, T. (December 23, 2024). 7 indications for GLP-1s beyond weight loss. *BioSpace*. Retrieved January 2, 2025, from <https://www.biospace.com/drug-development/7-indications-for-glp-1s-beyond-weight-loss>.

7. Jha, M. (February 5, 2025). Tirzepatide for obesity and meth use disorder. *Clinicaltrials.gov*. Retrieved April 9, 2025, from <https://clinicaltrials.gov/study/NCT06745128>.

### Side effects and route of administration.

Currently, side effects are a primary concern for prescribers and patients alike. As the health care community gains more experience with GLP-1s, patients and prescribers may become better able to find strategies to mitigate uncomfortable side effects, including nausea, vomiting, constipation, gastroparesis, dehydration, and gallstones.<sup>8</sup> In addition, more recent research has linked these medications to rare forms of vision loss.<sup>9</sup> Over time, greater availability and improved new molecules that allow flexibility with respect to routes of administration (e.g., oral or injection) and frequency (e.g., daily, twice daily, or weekly) may make for improved take-up rates and persistency. To the degree that advances in knowledge improve patient experience, GLP-1 adherence would also improve.

### Other therapeutic classes.

The body of knowledge relating to understanding metabolic pathways is ever-expanding. Therefore, GLP-1s could potentially be eclipsed in the future by new treatments. For instance, researchers may one day develop a cost-effective gene therapy that could eliminate the need for ongoing GLP-1 treatment. It is also possible that researchers may one day discover other pathways or mechanisms that lead to entirely new classes of medications.

## INFLUENCED BY PROVIDERS

### Clinical guidelines and prescribing patterns.

Clinical guidelines and prescribing patterns are a key driver of utilization. Clinical guidelines may be published by organizations such as the American Diabetes Association (ADA), the American College of Endocrinology (ACE), and the American Academy of Sleep Medicine (AASM), to name a few. Clinical guidelines recommending treatment with GLP-1s will influence prescribing patterns, leading to an increase in the number of individuals using GLP-1s. Additionally, prescribing patterns can shift even in the absence of clinical guidelines as some physicians are comfortable prescribing medications even in the absence of specific guidance.<sup>10</sup> Further, as physicians gain more experience treating patients with GLP-1s, they may become more (or less) likely to prescribe these medications. They might also have an increased focus on medication adherence, outcomes, and side effects for these drugs. Each of these dynamics can increase (or decrease) the number of individuals taking GLP-1s. Further, while current clinical guidelines recommend that GLP-1s should be taken indefinitely, we cannot predict with certainty that this will remain best practice. For example, a study in *Diabetes Therapy* indicated that GLP-1 deprescription may be possible and sustainable.<sup>11</sup> If GLP-1 deprescription becomes widely practiced, this would decrease the number of utilizers.

### Third-party or telehealth prescribers.

Some telehealth clinics provide broad access to GLP-1s through virtual visits with prescribers.<sup>12</sup> Patients may be more likely to obtain GLP-1 prescriptions when they have access to a prescriber at a flexible time and place. Furthermore, these providers promote self-pay options, thereby allowing patients to access a prescriber outside of their health insurance.

8. Novak, S. (December 27, 2024). Expert tips for managing GLP-1 medication side effects. *Medscape Medical News*. Retrieved January 3, 2025, from <https://www.medscape.com/viewarticle/expert-tips-managing-glp-1-medication-side-effects-2024a1000p8l>.

9. Hathaway, J. et al. (July 3, 2024). Risk of nonarteritic anterior ischemic optic neuropathy in patients prescribed semaglutide. *JAMA Ophthalmology*, 142(8), 732–739. Retrieved March 5, 2025, from <https://jamanetwork.com/journals/jamaophthalmology/fullarticle/2820255>.

10. Stafford, R. (April 3, 2008). Regulating off-label drug use – Rethinking the role of the FDA. *New England Journal of Medicine*, 358(14). Retrieved June 30, 2025, from <https://www.nejm.org/doi/full/10.1056/NEJMp0802107>.

11. McKenzie, A. & Athinarayanan, S. (February 29, 2024). Impact of glucagon-like peptide 1 agonist deprescription in type 2 diabetes in a real-world setting: A propensity score matched cohort study. *Diabetes Therapy*, 15, 843–853. Retrieved January 2, 2025, from <https://link.springer.com/article/10.1007/s13300-024-01547-0>.

12. Landi, H. (February 13, 2025). Primary care doctors concerned about telehealth GLP-1 boom: Survey. *Fierce Healthcare*. Retrieved June 30, 2025, from <https://www.fiercehealthcare.com/providers/primary-care-doctors-concerned-about-patient-risks-telehealth-prescribers-glp-1s-survey>.

## INFLUENCED BY MANUFACTURERS

### Advertising and promotion.

Direct-to-consumer advertising (DTCA) has contributed to increased use of GLP-1s.<sup>13</sup> Drug manufacturers typically increase expenditure on DTCA during key events, such as when a drug is approved to treat additional conditions. Alternatively, manufacturers may decrease expenditure following a generic launch.<sup>14</sup> GLP-1s can be considered the first drug class to drive both off-label and on-label use from social media posts, marketing, and promotions. Social media likely contributed to increased utilization and general acceptance.<sup>15</sup>

### Generic launches.

Coverage and formulary placement will be driven, in part, by the availability of generics. Although we currently anticipate a generic GLP-1 launch within 10–15 years (see Figure 4 for the expected GLP-1 generic version pipeline), the timing and availability of generics can be uncertain. This uncertainty may be more considerable for medications with somewhat complex manufacturing techniques. GLP-1s require complex manufacturing techniques due to the large size of GLP-1 molecules. Typically, generic launches are associated with lower out-of-pocket costs for patients and lower unit costs. Therefore, the greater availability of generics would generally increase the number of individuals taking GLP-1s.

FIGURE 4: GLP-1 GENERIC PIPELINE<sup>16</sup>

| ACTIVE INGREDIENT | BRAND NAME | APPROVED INDICATION       | DRUG TYPE                       | PATENT LOSS DATE | EXPECTED GENERIC LAUNCH DATE |
|-------------------|------------|---------------------------|---------------------------------|------------------|------------------------------|
| Exenatide         | Byetta     | Type 2 diabetes           | GLP-1 receptor agonist          | 2021             | 2025                         |
| Albiglutide       | Tanzeum    | Type 2 diabetes           | GLP-1 receptor agonist          | 2022             | N/A (discontinued)           |
| Liraglutide       | Victoza    | Type 2 diabetes           | GLP-1 receptor agonist          | 2022             | 2024                         |
| Lixisenatide      | Adlyxin    | Type 2 diabetes           | GLP-1 receptor agonist          | 2023             | N/A (discontinued)           |
| Exenatide         | Bydureon   | Type 2 diabetes           | GLP-1 receptor agonist          | 2027             | 2027                         |
| Dulaglutide       | Trulicity  | Type 2 diabetes           | GLP-1 receptor agonist          | 2027             | 2027                         |
| Semaglutide       | Ozempic    | Type 2 diabetes           | GLP-1 receptor agonist          | 2032             | 2032                         |
| Semaglutide       | Rybelsus   | Type 2 diabetes           | GLP-1 receptor agonist          | 2034             | 2034                         |
| Semaglutide       | Wegovy     | Chronic weight management | GLP-1 receptor agonist          | 2041             | 2041                         |
| Tirzepatide       | Mounjaro   | Type 2 diabetes           | Dual GIP/GLP-1 receptor agonist | 2041             | 2041                         |
| Tirzepatide       | Zepbound   | Chronic weight management | Dual GIP/GLP-1 receptor agonist | 2039             | 2039                         |
| Liraglutide       | Saxenda    | Chronic weight management | GLP-1 receptor agonist          | 2037             | 2037                         |

13. Adams, B. (September 23, 2023). As Novo Nordisk boosts Wegovy, Ozempic ad spend, analysis finds “a rising tide lifts all boats” for diabetes, weight-loss drugs. *Fierce Pharma*. Retrieved June 30, 2025, from <https://www.fiercepharma.com/marketing/novo-nordisk-boosts-wegovy-ozempic-ad-spend-analysis-finds-rising-tide-lifts-all-boats>.

14. U.S. Government Accountability Office. (May 2021). Prescription drugs: Medicare spending on drugs with direct-to-consumer advertising. GAO-21-380. Retrieved January 2, 2025, from <https://www.gao.gov/products/gao-21-380>.

15. Basch, C.H., Narayanan, S., Tang, H., Fera, J. & Basch, C.E. (September 25, 2023). Descriptive analysis of TikTok videos posted under the hashtag #Ozempic. *Journal of Medicine, Surgery, and Public Health*, 1. Retrieved June 30, 2025, from <https://www.sciencedirect.com/science/article/pii/S2949916X23000130>.

16. Figure 2 is derived from the authors' analysis of the FDA Orange Book data and Milliman internal research. The patent loss date corresponds to the latest patent expiration date published in the FDA Orange Book as of August 2026. Generic versions of brand drugs are generally planned to launch immediately upon patent expiration unless they are impacted by litigation, regulations, business factors, or new patents granted. We also relied upon Milliman internal research—namely, the Patent Loss Assumption Tool (PLAT). PLAT is a modeling resource that estimates the cost and utilization impacts of brand drug patent expirations. It is based upon market research and historical generic launches.

### **Self-pay and discount coupons.**

Our analysis only includes GLP-1 medications reimbursed through a prescription drug benefit, although we recognize that many individuals are obtaining these medications using cash or coupons. This dynamic appears to be especially prevalent in the context of manufacturing shortages, as evidenced by the FDA temporary authorization for compounding pharmacies to dispense compounded versions of these drugs. Many compounding pharmacies accept cash pay only, and this dynamic must therefore be considered in the forecast. Furthermore, patients are more likely to obtain these drugs using self-pay (cash) if they can obtain the drugs for a lower price than through a commercial drug benefit, which is possible for patients with high deductibles. The current and future availability of coupons will also influence consumer behavior.

## **INFLUENCED BY HEALTH PLANS AND PLAN SPONSOR DECISIONS**

### **Coverage and formulary placement.**

Over the course of the next 10–15 years, we anticipate that coverage of GLP-1s for weight loss on commercial formularies will become inevitable, particularly as generics launch. While this assumption underlies the Markov model, plan sponsors may or may not retain flexibility in formulary design or plan coverage of certain FDA-approved indications of GLP-1s in the future. For example, plans may not cover weight loss, yet plans may be required to cover supplemental indications of weight-loss GLP-1s that treat comorbidities associated with being overweight (e.g., major adverse cardiovascular events). Additionally, new indications for GLP-1s could be expected that may be essential for coverage by plans (e.g., Alzheimer’s disease). Finally, legislative mandates may require commercial coverage of GLP-1s for weight loss for certain populations. Depending on the full list of conditions GLP-1s are ultimately approved for and the emerging pharmaeconomics of this class of medication, it is conceivable that plan sponsors could take different paths with respect to GLP-1 coverage. By emerging pharmaeconomics, we are referring to the perceived balance of cost and clinical benefits which may change over time.

### **Utilization management and responsible prescribing.**

Pharmacy utilization management (UM) refers to a set of strategies and processes used by health plans, pharmacy benefit managers (PBMs), and healthcare organizations to ensure that prescription medications are used appropriately, safely, and cost-effectively. These practices aim to balance patient care with financial sustainability across the healthcare system but can also restrict access. UM includes prior authorization, step therapy, and quantity limits. To the extent that PBMs either tighten (or loosen) requirements around UM of GLP-1s, we expect to see a decrease (or increase) in GLP-1 utilization. In addition, employers balance the cost of these drugs against their clinical benefits and the perceived value to their employees. In other words, some plan sponsors believe that coverage under the FDA criteria (a BMI of 30 or above for those without comorbidities) is too broad.<sup>17</sup> Plan sponsors may respond by tightening coverage, and some payers have recently updated UM requirements so individuals would not be able to obtain coverage through the payers’ prior authorization rules despite meeting FDA criteria.<sup>18</sup> In this example, individuals with Class I and Class II obesity would not be able to have a GLP-1 prescription covered by insurance. To achieve similar outcomes as UM, several PBMs are currently implementing responsible prescribing techniques through a concept some refer to as an obesity center of excellence.<sup>19</sup> This approach encourages prescribers to present patients with a range of options prior to writing a prescription for GLP-1s for weight loss. While technically feasible, we have not seen the industry broadly adopt a UM approach that coordinates electronic medical records of diagnosis codes and pharmacy prior authorization. This approach would improve appropriate use and may even reduce administrative costs. Both UM and responsible prescribing may make coverage of GLP-1s more palatable for employers because they would have a broader range of options than simply covering or not covering GLP-1s for weight loss.

17. McGough, M., Lo, J., Tevis, D., Rae, M. & Cox, C. (September 5, 2024). How many adults with private health insurance could use GLP-1 drugs. *Peterson-KFF Health System Tracker*. Retrieved August 27, 2025, from <https://www.healthsystemtracker.org/brief/how-many-adults-with-private-health-insurance-could-use-glp-1-drugs/>.

18. Blue Shield of California. (November 2024). Weight-loss medication coverage change fact sheet. Retrieved April 9, 2024, from <https://www.blueshieldca.com/content/dam/bsca/en/provider/docs/Weight-Loss-Drug-Exclusion-Fact-Sheet.pdf>.

19. Naber, J., Barrington, A. & Platt, B. (February 2024). Employers and targeted obesity care: Exploring the concept of an obesity center of excellence. Milliman white paper. Retrieved January 2, 2025, from [https://www.milliman.com/-/media/milliman/pdfs/2024-articles/2-5-24\\_employers-and-targeted-obesity-care\\_center-of-excellence.ashx](https://www.milliman.com/-/media/milliman/pdfs/2024-articles/2-5-24_employers-and-targeted-obesity-care_center-of-excellence.ashx).

For example, an employer may choose to cover GLP-1s for weight loss only when the patient meets the clinical definition of Class II or Class III obesity rather than Class I obesity. Alternatively, an employer may choose to implement an obesity center of excellence along with other programs aimed at metabolic health. It can be assumed that at least some employers will choose to cover GLP-1s with such programs in place.

### **Drug shortages.**

The possibility of continued or future shortages would likely reduce the number of individuals taking GLP-1s covered by insurance, including those initiating therapy. This dynamic could postpone the date at which GLP-1 utilization plateaus.

## **INFLUENCED BY OTHER ENTITIES AND FACTORS**

### **Halo effect from potential Medicare coverage.**

There is potential for Medicare Part D and Medicaid to begin covering GLP-1s for weight-loss indications in the future. While the Centers for Medicare and Medicaid Services (CMS) chose not to cover these medications beginning on January 1, 2026, as initially proposed in the 2026 Proposed Rule (CMS-4208-P), this decision could be revisited in future years. Recently, CMS was reported to have reconsidered this proposal.<sup>20</sup> It is possible that federal coverage would shift perceptions of plan sponsors regarding the benefits of such medications, which should further increase commercial coverage. Another phenomenon known as authority bias may influence the decision-making and opinions of authoritative entities—that is, an employer may be more likely to cover a therapy if CMS covers it. This dynamic could lead to greater public acceptance and awareness of these medications and an increase in the number of individuals taking GLP-1s.

### **Prevalence of obesity and related disorders.**

The prevalence of obesity has generally been increasing in the United States since the late 1970s. Obesity is a major risk factor for type 2 diabetes.<sup>21</sup> The Markov model implicitly assumes a direct link between the prevalence of obesity, through the proxy of type 2 diabetes prevalence, and GLP-1 utilization. To the extent that the obesity epidemic stabilizes more quickly than implied in our underlying forecast or even subsides, it would be natural to infer that the number of individuals using GLP-1s would decrease overall. Emerging research suggests that the prevalence of obesity actually decreased during 2023, the first time in a decade.<sup>22</sup>

## **Results**

Figure 5 below provides a summary of the distribution of members in the distant future. In our middle (low) and middle (high) scenarios, we estimate that 7.9% to 12.7% of the total commercial population will be using GLP-1s for weight loss in the distant future. As can be seen in Figure 5, the number of members with a history of obesity is lower than estimates from the U.S. Centers for Disease Control and Prevention (CDC) and elsewhere, as referenced in this paper. This discrepancy is explained by at least two dynamics. First, members that do not seek health care will not have any historical data, regardless of whether the individual does or does not meet the clinical definition for obesity. Nearly one-third of Americans do not have access to a usual source of primary care, and therefore many people may have an unreported condition.<sup>23</sup> Second, providers may not include diagnosis codes for obesity when submitting administrative claims data. Therefore, we classify many individuals as healthy in the Markov model despite a history of obesity.

20. Manalac, T. (August 4, 2025). CMS mulls about-face in coverage of GLP-1 treatments for obesity: Report. *BioSpace*. Retrieved August 27, 2025, from <https://www.biospace.com/policy/cms-mulls-about-face-in-coverage-of-glp-1-treatments-for-obesity-report>.

21. Mitchell, N., Catenacci, V., Wyatt, H. & Hill, J. (December 2011). Obesity: Overview of an epidemic. *Psychiatric Clinics of North America*, 34(4), 717–732. Retrieved January 2, 2025, from <https://pubmed.ncbi.nlm.nih.gov/articles/PMC3228640/>.

22. Rader, B., Hazan, R. & Brownstein, J. (December 13, 2024). Changes in adult obesity trends in the US. *JAMA Health Forum*, 5(12), e243685. Retrieved January 3, 2025, from <https://jamanetwork.com/journals/jama-health-forum/fullarticle/2827712>.

23. National Association of Community Health Centers. (February 2023). Closing the primary care gap: How community health centers can address the nation's primary care crisis. Retrieved June 30, 2025, from [https://www.nachc.org/wp-content/uploads/2023/06/Closing-the-Primary-Care-Gap\\_Full-Report\\_2023\\_digital-final.pdf](https://www.nachc.org/wp-content/uploads/2023/06/Closing-the-Primary-Care-Gap_Full-Report_2023_digital-final.pdf).

However, our Markov model and our assumptions account for this because the Markov model has a state for individuals without a history of obesity receiving treatment with GLP-1s. In our model, individuals without a history of obesity account for almost one-quarter of the nondiabetic population using GLP-1s. We assume that these patients met clinical criteria to obtain GLP-1s, although their medical history was not fully documented. Our model forecasts that this trend will continue into the future—some portion of the population will continue to have incomplete medical history in administrative claims data. Therefore, the Markov model's structure, form, and underlying assumptions are sufficient to forecast GLP-1 utilization, although the forecast for the rate of obesity does not match CDC data.

FIGURE 5: RESULTS IN THE DISTANT FUTURE

| AVERAGE MONTHLY DISTRIBUTION OF MEMBERS                           | LOW         | MIDDLE (LOW) | MIDDLE (HIGH) | HIGH         | HIGHEST      |
|---|-------------|--------------|---------------|--------------|--------------|
| <b>Start</b>  | 2.0%        | 2.0%         | 2.0%          | 2.0%         | 2.0%         |
| <b>End</b>  | 2.0%        | 2.0%         | 2.0%          | 2.0%         | 2.0%         |
| <b>Healthy, not on drug</b>                                       | 69.6%       | 68.2%        | 65.0%         | 66.0%        | 64.1%        |
| <b>Obese, not on drug</b>   | 13.6%       | 13.8%        | 13.5%         | 10.5%        | 8.9%         |
| <b>Diabetes, not on drug</b>                                      | 6.7%        | 6.3%         | 5.3%          | 3.8%         | 3.4%         |
| <b>Healthy, on drug</b>   | 0.5%        | 0.6%         | 0.9%          | 2.0%         | 2.6%         |
| <b>Obese, on drug</b>   | 2.0%        | 2.7%         | 4.8%          | 6.8%         | 9.3%         |
| <b>Diabetes, on drug</b>  | 3.5%        | 4.3%         | 6.5%          | 6.9%         | 7.7%         |
| <b>BY CONDITION</b>   |             |              |               |              |              |
| <b>Start/end</b>  | 4.1%        | 4.1%         | 4.0%          | 4.0%         | 4.0%         |
| <b>Healthy (no history)</b>                                       | 70.1%       | 68.8%        | 65.9%         | 68.0%        | 66.7%        |
| <b>History of obesity</b>   | 15.7%       | 16.4%        | 18.2%         | 17.3%        | 18.2%        |
| <b>History of diabetes</b>  | 10.2%       | 10.6%        | 11.8%         | 10.7%        | 11.1%        |
| <b>PROPORTION TAKING GLP-1S IN DISTANT FUTURE:</b>                |             |              |               |              |              |
| <b>Percentage of healthy taking GLP-1s</b>                        | 0.8%        | 0.9%         | 1.3%          | 2.9%         | 3.9%         |
| <b>Percentage of those with history of obesity taking GLP-1s</b>  | 13.0%       | 16.3%        | 26.2%         | 39.4%        | 51.2%        |
| <b>Percentage of those with history of diabetes taking GLP-1s</b> | 34.4%       | 40.4%        | 55.0%         | 64.6%        | 69.5%        |
| <b>Percentage of total membership taking GLP-1s</b>               | <b>6.3%</b> | <b>7.9%</b>  | <b>12.7%</b>  | <b>16.3%</b> | <b>20.4%</b> |

1. The percentage of those with diagnosis data for obesity and diabetes is based upon administrative claims data and does not reflect all individuals with these diseases. Some individuals may not have been diagnosed, and other individuals may have been diagnosed without the diagnosis being submitted in the claims data. Therefore, care should be taken in interpreting the results because many individuals that our model marks as healthy may in fact be overweight with comorbidities.
2. The distant future represents a time period when there is no anticipated change in the distribution of members; that is, the Markov model has stabilized. For this model and under these sets of assumptions, it would be appropriate to think of this time frame as the late 2030s.

## Estimating future costs

Figure 6 provides a range of future costs based on the projected utilizers. While the future net cost of GLP-1 medications is highly uncertain, we provide some ranges to illustrate the potential impact to plan sponsors in the distant future when generics are expected to be widely available. Our range of estimated unit costs is grounded in an economic evaluation of manufacturing costs.<sup>24</sup>

**FIGURE 6: 2037+ ESTIMATES OF MONTHLY COSTS FOR GLP-1S  
(GENERIC COVERAGE ONLY, PER MEMBER PER MONTH, COMMERCIAL POPULATION)**

| UNIT COSTS                     | LOW    | HIGH    |
|--------------------------------|--------|---------|
| <b>\$50 per 30-day supply</b>  | \$3.17 | \$8.17  |
| <b>\$140 per 30-day supply</b> | \$8.87 | \$22.88 |

1. These estimates are valid for typical employer-sponsored insurance and are intended to represent a range for the entire commercial market rather than a range for specific employers. A specific employer may fall outside these ranges. These estimates are not intended for plans with very low cost sharing (such as public employer plans or unions), Veteran Health benefits, or other health insurance programs.
2. Monthly costs include all GLP-1s regardless of whether indicated for management of diabetes, chronic weight management, or otherwise.
3. These estimates assume full coverage of GLP-1s for weight loss and that all dispensed drugs are generics. Therefore, there would be no pharmacy rebates. Even with increasing availability of generics, we anticipate that some brands would still be dispensed; therefore, actual costs are likely to be higher but partially offset by pharmacy rebates.
4. Low estimate assumes 6.3% of the population takes GLP-1s each month; high estimate assumes 16.3% (consistent with Figure 5). The estimated cost is the unit cost multiplied by the percentage of the population taking GLP-1s.

## Drugs included in this study

For our analysis, we identified and included all currently available GLP-1s. This includes medications indicated for the management of type 2 diabetes and medications indicated for chronic weight management and other indications. This section provides more detail on each subclass included in our analysis, along with common example medications.

**GLP-1 receptor agonists** mimic the action of the incretin hormone GLP-1, which works in multiple ways in the human body: increasing insulin secretion and sensitivity, slowing down gastric emptying, increasing satiety, and decreasing hepatic glucose production. The result of these various effects on the body is lower blood sugar levels and weight loss. Common products include dulaglutide (Trulicity) and semaglutide (Ozempic and Rybelsus). This subclass also includes tirzepatide (Mounjaro) which is a dual-action gastric inhibitory polypeptide (GIP) and GLP-1 receptor agonist. The first GLP-1 receptor agonist, exenatide (Byetta), was approved by the FDA in 2005, and long-acting GLP-1s with additional positive comorbidity outcomes began to be approved in 2014.

**Anti-obesity GLP-1 receptor agonists** are bioequivalent to GLP-1 receptor agonists but are specifically approved for weight management. They help reduce appetite and increase feelings of fullness, which can lead to weight loss. Common products include liraglutide (Saxenda), semaglutide (Wegovy), and tirzepatide (Zepbound). This subclass also includes dual-action GIP and GLP-1 receptor agonists. Because these products are bioequivalent to the antidiabetic GIP and GLP-1 medications and because of the possibility of off-label prescribing, we have included these medications in our trend study. Similarly, we recognize that GLP-1 receptor agonists indicated for type 2 diabetes may also be prescribed and utilized for weight loss rather than the labeled indication. The first medication in the anti-obesity subclass, Saxenda, was approved for weight loss in 2014.<sup>25</sup>

24. Barber, M., Gotham, D., Bygrave, H. & Cepuch, C. (March 27, 2024). Estimated sustainable cost-based prices for diabetes medications. *JAMA Network Open*, 7(3), e243474. Retrieved February 17, 2025, from <https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2816824>.

25. Tan, Q., Akindehin, S., Orsso, C., Waldner, R., DiMarchi, R., Müller, T. & Haqq, A. (February 28, 2022). Recent advances in incretin-based pharmacotherapies for the treatment of obesity and diabetes. *Frontiers in Endocrinology*, 13, 838410. Retrieved December 8, 2024, from <https://doi.org/10.3389/fendo.2022.838410>.

## The Markov model

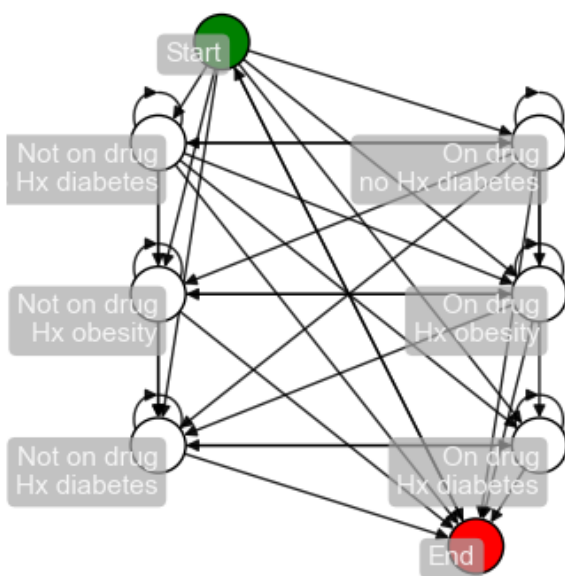
The intent of the Markov model is to provide insights into when a commercial group covering GLP-1s for weight loss may stop seeing large annual increases in GLP-1 utilization and cost. To develop our long-range forecast of GLP-1 utilization, we developed a Markov model where each state represents a combination of disease status and whether the enrollee is currently taking GLP-1 medications.

Markov models are a class of mathematical models that provide a robust framework for modeling stochastic processes, particularly where outcomes are determined by a series of probabilistic events. These models are characterized by their ability to represent transitions between different states over time, where future states depend only on the current state and not on the sequence of events that preceded it. This property, known as the Markov property, simplifies the complexity of modeling dynamic systems and makes Markov models highly suitable for various applications in healthcare and actuarial science.

We are aware of other projects using Markov models. These models are often used to develop premium estimates for disability insurance. These models can represent the healthy status of an individual and whether they have returned to work and at what capacity. Other actuaries at Milliman have used this modeling approach to forecast utilization of Hepatitis C drugs.

In a Markov model, a system is divided into discrete states, and transitions between these states occur at specific intervals, governed by transition probabilities. These probabilities can be derived from empirical data or clinical studies, making the models highly adaptable to real-world scenarios. The states typically represent different health conditions, treatment stages, or disease progressions, and the transitions capture the likelihood of moving from one state to another within a given time frame.

FIGURE 7: A MARKOV MODEL FOR A COMMERCIAL POPULATION



1. **Hx obesity** indicates the enrollee has a history of obesity. **Hx diabetes** indicates the enrollee has a history of diabetes.
2. **Start** represents the first month an individual enters our data set, which is after 12 months of continuous insurance coverage so that we may establish a medical history. **End** represents the last month of insurance coverage.

For our Markov model, each transition occurs at an interval of one month. The transition probabilities presented in this paper are derived from medical and pharmacy claims data, as well as enrollment data. The distribution of members in the next time period is evaluated by multiplying the current distribution of members by the transition matrix.

There are several features of Markov models that make this approach a helpful framework for modeling long-term utilization of GLP-1 medications.

- **Capturing disease progression.** A Markov model can effectively represent the progression of disease as a state transition. The prevalence of diabetes has been generally increasing in the United States over the past few decades, which is a contributing factor to the increased use of antidiabetic medications such as GLP-1s in a commercial population.<sup>26</sup> This is particularly important because enrollees with a history of diabetes are more likely to initiate utilization of GLP-1s and are more likely to adhere to GLP-1 therapy.
- **Incorporation of patient behavior.** Patient behavior could impact whether members discontinue use of GLP-1s. For instance, certain patients may discontinue therapy due to cost concerns, while others may discontinue therapy due to side effects. The Markov model can address whether an enrollee is taking medication at discrete points of time and reflect that many individuals will not continue to use medication.
- **Use of real-world data.** Markov models can be calibrated with real-world data even if the system has not yet stabilized. To develop our framework, we partially relied on the claims databases described below. However, we believe that the transition probabilities have not yet stabilized, and therefore we have developed a forecast based upon a blend of real-world data and judgment.
- **Incorporation of utilization data.** Our underlying data includes not just the number of individuals taking these medications but also the number of 30-day equivalent scripts. The inclusion of this utilization data can make Markov models helpful for forecasting health care costs, which are driven by the number of scripts filled.
- **Flexibility.** Markov models can be fitted and adapted to emerging data as it becomes available. For example, the probability of continuing to adhere to the medication may be different as newer medications with fewer side effects become available. The model manages this dynamic well.
- **Probabilistic nature.** The probabilistic transitions align well with uncertainty related to disease progression and medication adherence for each individual. By capturing and modeling this uncertainty, the model can provide realistic projections of future health states.
- **Computational efficiency.** Markov models can simulate future events without a need for extensive computing power. Our forecasting model was built in Excel and can simulate 10 years of outcomes instantaneously.

Markov models have many strengths and weaknesses. A strength of some Markov models is that it is possible to calculate its stationary distribution using linear algebra.<sup>27</sup> In simple terms, imagine freezing time after observing a population for many years. The stationary distribution would show the fraction of people, on average, in each state shown in Figure 7. Using the same assumptions as those shown in Figure 1, the stationary distributions for our five Markov models estimate that roughly 6–20% of members will be utilizing GLP-1 drugs and 10–12% of members will have type 2 diabetes in the distant future, assuming that our transition probabilities are constant over time.

Another interesting feature of the stationary distribution is that it allows for rapid testing of sensitivities. For example, two of the most critical assumptions for the long-range forecast are the take-up rate of these drugs for individuals without diabetes and the persistency of these drugs for such individuals. We adjust the take-up rate for these drugs using a multiplier that accounts for both increased coverage and increased popularity. Interestingly, increasing this multiplier by a factor of 2 does not double the long-term forecast. This result is driven by the many states that members can take and interacts with persistency, illustrating another core feature of a Markov model. In practice,

26. Rogers, J. & Dewey, B. (December 19, 2024). Understanding the cost dynamics of antidiabetic medications: A trend analysis (2016-2024). Milliman white paper. Retrieved December 8, 2024, from <https://www.milliman.com/en/insight/cost-antidiabetic-medications-trend-analysis>.

27. Alridge, M. (2021). *Section 10, Stationary distributions* [PowerPoint slides]. Retrieved February 2, 2025, from <https://mpaldrige.github.io/math2750/S10-stationary-distributions.html>.

members stop and start medications each month, so doubling members trying the medications for the first time will not necessarily double the total utilization of drugs.

**FIGURE 8: PERCENTAGE OF MEMBERS TAKING GLP-1 MEDICATIONS IN THE DISTANT FUTURE (SENSITIVITY)**

|   |     | MONTHLY PERSISTENCY FOR MEMBERS WITHOUT DIABETES |       |       |       |       |
|---|-----|--|-------|-------|-------|-------|
|   |     | 91%  | 92%   | 93%   | 94%   | 97%   |
| MULTIPLIER - ACCOUNTS FOR FULL COVERAGE AND INCREASED POPULARITY OF THE DRUGS | 0.5 | 6.2%   | 6.2%  | 6.3%  | 6.5%  | 7.3%  |
|   | 1.0 | 6.8%   | 7.0%  | 7.1%  | 7.3%  | 8.8%  |
|   | 2.0 | 8.1%   | 8.3%  | 8.6%  | 9.0%  | 11.3% |
|   | 4.0 | 10.4%  | 10.8% | 11.2% | 11.9% | 15.4% |
|   | 8.0 | 14.3%  | 14.9% | 15.6% | 16.5% | 21.2% |

A key weakness of this methodology is the expectation that there will be a shift in treatment patterns or in the progression of diabetes at some point in the future. This would suggest a change in the probability of transitioning from one state to another. Unfortunately, Markov models are intended to be simple. Thus, Markov models cannot manage temporal changes in the probability of transitioning from one Markov state to another, which means that our stationary distribution shown above will likely not be an accurate representation of long-term behavior. On the other hand, microsimulation models can reflect a greater level of complexity and may be better suited for dynamic interactions. In addition, as discussed above, while real-world data may be used to populate these models, there are any number of reasons why future changes would not be reflected in the latest real-world data—for example, coverage changes or generic launches.

An alternative approach to the Markov model may be to use time-varying transition probabilities. This approach, for instance, could use a different transition matrix each year. In this manner, modeling increasing coverage or popularity of the drugs could more precisely model the path these drugs may take for the entire commercial market. Because our goal is to determine when the drugs may stop increasing for an employer already covering these drugs, we made the decision to simply adjust our transition matrix to assume full coverage immediately. This assumption accounts for the significant increase from 2024 to 2025.

Another feature of Markov models is that the probability of transitioning from one state to another does not depend on the history of past states. For this reason, Markov models may be described as stateless. To illustrate, the probability of an individual starting a GLP-1 medication is the same in the Markov model regardless of how many times that individual has started GLP-1s. That said, additional states may be introduced to model the complexity of state history and state transitions. For example, it would be possible to add additional states that assign different transition probabilities to individuals who have a history of taking the medication. To the degree that this population has a different likelihood of starting or stopping medication, this may lead to different results.

## Data sources

We relied on Milliman’s proprietary health research databases to complete this study, along with the assumptions discussed throughout this white paper. Our research databases allow for the tracking of de-identified patients across multiple years because continuous enrollment is critical for this study. Milliman has assembled a multiyear, multi-line-of-business, longitudinal claims and enrollment data structure for use in its product production, internal research, and client engagements. National and regional health plans contribute their annual enrollment and claims detail. The number of unique annual lives represented in this research data is between 80 and 100 million members, depending on the year, and includes commercial, individual, Medicaid, Medicare Advantage, and Medicare Supplement members’ claims and enrollment across all states.

National Drug Codes (NDCs) for relevant drugs were identified using the Wolters Kluwer Medi-Span Master Drug Data Base v2.5 based upon the generic product identifier (GPI), as discussed below. More details about our approach and handling of classes can be found in the Methodology section below.

## Evaluating the Markov model using data-driven assumptions

A key feature of Markov models is that the transition probabilities are consistent over time. During our analysis, we observed that the transition probabilities were not stable (i.e., the probabilities of moving among stages varies depending on the periodicity of the underlying data). In fact, the most recent available data suggests an ever increasing propensity to start GLP-1s, as well as to continue to use GLP-1s. To illustrate these differences, we developed Figure 9 below. While Figure 1 shows our low, middle (low), middle (high), high, and highest estimates of the GLP-1 plateau, Figure 9 shows estimates of the GLP-1 plateaus if we used unaltered, data-driven assumptions from 2019 to 2023. Each line represents a forecast informed by the underlying data from the relevant year, where the transitions probabilities are stable throughout the entire forecast. Historical data is based upon actual experience.

**FIGURE 9: LONG-RANGE ESTIMATES BASED UPON RAW DATA FROM 2019 TO 2023 - GLP-1 PLATEAU AMONG UTILIZERS**

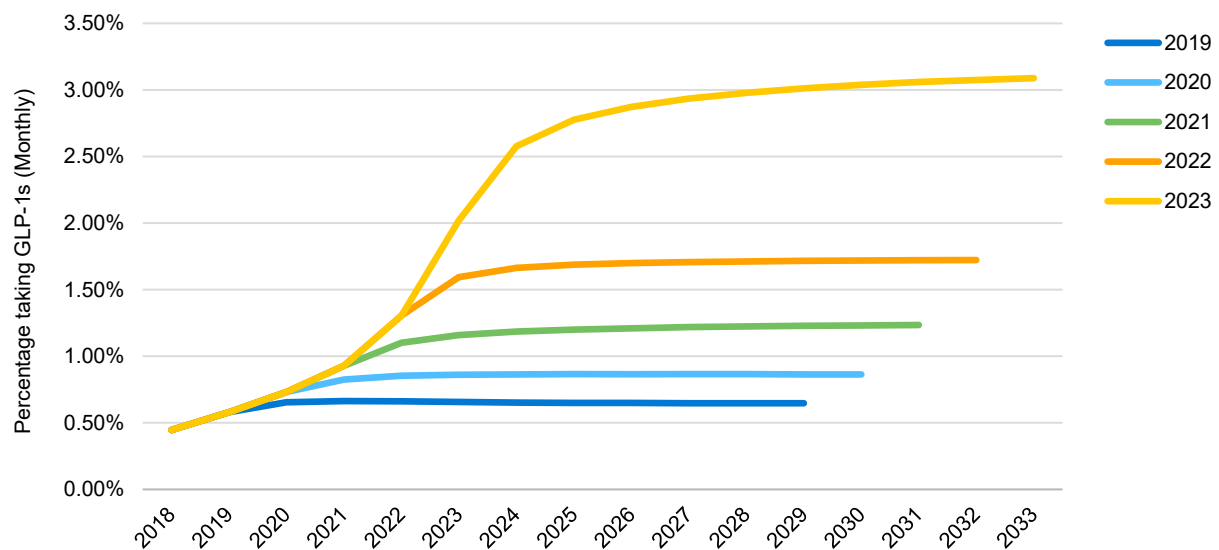


Figure 9 shows that the GLP-1 plateau continues to be pushed further and further out into the future as more recent real-world data is used to set transition probabilities. This is consistent with many of the dynamics discussed throughout this white paper that would lead to a shift toward a higher level of plateau.

## Methodology

### COMMERCIAL COVERAGE OF ANTI-OBESITY MEDICATIONS

Many commercial payers did not and do not cover anti-obesity medications. As a result, the probability of initiating therapy, especially for individuals without a history of diabetes, may be difficult to ascertain. For simplicity, we assumed that the propensity to start GLP-1s for the population without diabetes would be higher than observed in 2024 data. We obtained this result by taking one divided by an estimated commercial coverage rate of 47.7% for a factor of 2.1. In other words, we are assuming that the likelihood of initiating therapy for GLP-1s for weight loss is directly related to increased coverage.

### DRUG SHORTAGES

The United States has experienced shortages for some medications in recent years, making it challenging to assess the probability of initiating therapy of a medication that is scarce in supply. GLP-1s have experienced shortages since 2022, which had not been fully resolved as of October 2024.<sup>28</sup> While these shortages have been resolved as of May 2025, our underlying data includes time periods for which shortages influenced treatment patterns. We considered several approaches for adjusting our historical data to account for drug shortages. Given that prescribing patterns have shifted to GLP-1s in more recent years, such as 2022 and 2023 (Figure 9), we are relying on 2024 experience with shortages in effect rather than older data without shortages. Using the older data without shortages would have counterintuitively resulted in a lower level of plateau.

### POPULARITY OF GLP-1S AND OFF-LABEL PRESCRIBING

In addition to considering coverage in our underlying data and drug shortages, we must consider the myriad of other factors that may influence the rate at which patients use GLP-1s. As discussed, our underlying reference may not fully reflect the future popularity of GLP-1s; for example, we may expect prescribing patterns to shift with further increased awareness. On the other hand, some patients without coverage for GLP-1s for weight loss may have had access to these drugs due to off-label prescribing in the base data. As discussed earlier, we set assumptions to reflect the overall increased popularity of these drugs. These factors increased the take-up rate for these drugs.

### CHANGE IN PRESCRIBING PATTERNS

As mentioned above, prescribing patterns for patients diagnosed with type 2 diabetes changed in the 2022 edition of the ADA's *Standards of Care in Diabetes*. Such a change would certainly be expected to influence the probability of starting therapy, particularly for those with a history of diabetes. As such, we relied upon 2024 data as the most recent relevant source of information to set our assumptions.

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28. ASHP. Drug shortages list: Current drug shortage bulletins. Retrieved December 11, 2024, from <https://www.ashp.org/drug-shortages/current-shortages/drug-shortages-list?page=CurrentShortages>.

## Data collection

To be included in our study, we required that an individual have continuous enrollment for 12 months to establish a history based on medical claims. Individuals must have coverage for pharmacy benefits and medical benefits. An individual enters our start state during the thirteenth month of enrollment. An individual enters our end state in their last month of enrollment data available within our databases.

To identify drugs for this study, we filtered drugs in Medi-Span based on their GPI. We included drugs that met one of the following conditions:

- GPI4 = 2717
- GPI6 = 612520, 612525

We considered an enrollee to be taking the drug if a prescription for any GLP-1 had been filled within 100 days (to allow for a 90-day supply and subsequent refills of medication) up until the enrollee's last prescription. After the enrollee's last prescription, we did not consider the enrollee to be taking the drug in the following months if there was a gap of greater than 100 days. We considered an enrollee to have a history of diabetes in any month during or after having an ICD-10 diagnosis code of E11, excluding services for diagnostic tests and labs using the range of procedure codes from 70000 to 89999. Similarly, for obesity, we used ICD-10 diagnosis codes of E66.0, E66.1, E66.2, E66.8, and E66.9.

As discussed above, we assumed that all commercial formularies would cover GLP-1s indicated for diabetes, weight management, and other conditions.

## Transition matrices

Our low, middle (low), middle (high), high, and highest estimates for transition probabilities are provided in Figures 10, 11, 12, 13, and 14 below. For reference, Figure 15 contains the unaltered data-driven transition probabilities using 2024 real-world data. The transition probabilities in Figure 15 result in the forecast based upon 2024 data, as shown in Figure 9. We simulated a population over 10 years. We assumed that individuals who enter the end state will transition to the start state during the following month.

FIGURE 10: LOW TRANSITION MATRIX (MONTHLY)

| FROM/TO                               | START   | END   | NOT ON DRUG    | NOT ON DRUG | NOT ON DRUG | ON DRUG        | ON DRUG    | ON DRUG     |
|---------------------------------------|---------|-------|----------------|-------------|-------------|----------------|------------|-------------|
|                                       |         |       | NO HX DIABETES | HX OBESITY  | HX DIABETES | NO HX DIABETES | HX OBESITY | HX DIABETES |
| <b>Start</b>                          | 0.00%   | 2.32% | 84.17%         | 7.45%       | 4.11%       | 0.19%          | 0.36%      | 1.40%       |
| <b>End</b>                            | 100.00% | 0.00% | 0.00%          | 0.00%       | 0.00%       | 0.00%          | 0.00%      | 0.00%       |
| <b>Not on drug<br/>No Hx diabetes</b> | 0.00%   | 2.12% | 97.50%         | 0.25%       | 0.05%       | 0.06%          | 0.02%      | 0.00%       |
| <b>Not on drug<br/>Hx obesity</b>     | 0.00%   | 1.96% | 0.00%          | 96.64%      | 0.22%       | 0.00%          | 1.16%      | 0.02%       |
| <b>Not on drug<br/>Hx diabetes</b>    | 0.00%   | 2.04% | 0.00%          | 0.00%       | 95.92%      | 0.00%          | 0.00%      | 2.04%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 2.13% | 4.63%          | 0.08%       | 0.04%       | 91.71%         | 0.85%      | 0.54%       |
| <b>On drug<br/>Hx obesity</b>         | 0.00%   | 1.86% | 0.00%          | 6.49%       | 0.03%       | 0.00%          | 91.20%     | 0.42%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 1.75% | 0.00%          | 0.00%       | 3.43%       | 0.00%          | 0.00%      | 94.81%      |

**FIGURE 11: MIDDLE (LOW) TRANSITION MATRIX (MONTHLY)**

| FROM/TO                            | START   | END   | NOT ON DRUG    | NOT ON DRUG | NOT ON DRUG | ON DRUG        | ON DRUG    | ON DRUG     |
|------------------------------------|---------|-------|----------------|-------------|-------------|----------------|------------|-------------|
|                                    |         |       | NO HX DIABETES | HX OBESITY  | HX DIABETES | NO HX DIABETES | HX OBESITY | HX DIABETES |
| <b>Start</b>                       | 0.00%   | 2.32% | 84.17%         | 7.45%       | 4.11%       | 0.19%          | 0.36%      | 1.40%       |
| <b>End</b>                         | 100.00% | 0.00% | 0.00%          | 0.00%       | 0.00%       | 0.00%          | 0.00%      | 0.00%       |
| <b>Not on drug<br/>Hx diabetes</b> | 0.00%   | 2.12% | 97.46%         | 0.28%       | 0.06%       | 0.06%          | 0.02%      | 0.00%       |
| <b>Not on drug<br/>Hx obesity</b>  | 0.00%   | 1.96% | 0.00%          | 96.50%      | 0.22%       | 0.00%          | 1.28%      | 0.03%       |
| <b>On drug<br/>Hx diabetes</b>     | 0.00%   | 2.04% | 0.00%          | 0.00%       | 95.70%      | 0.00%          | 0.00%      | 2.27%       |
| <b>Not on drug<br/>Hx diabetes</b> | 0.00%   | 2.13% | 3.71%          | 0.08%       | 0.04%       | 92.50%         | 0.95%      | 0.60%       |
| <b>On drug<br/>Hx diabetes</b>     | 0.00%   | 1.86% | 0.00%          | 5.19%       | 0.02%       | 0.00%          | 92.50%     | 0.42%       |
| <b>On drug<br/>Hx diabetes</b>     | 0.00%   | 1.75% | 0.00%          | 0.00%       | 2.75%       | 0.00%          | 0.00%      | 95.50%      |

**FIGURE 12: MIDDLE (HIGH) TRANSITION MATRIX (MONTHLY)**

| FROM/TO                               | START   | END   | NOT ON DRUG    | NOT ON DRUG | NOT ON DRUG | ON DRUG        | ON DRUG    | ON DRUG     |
|---------------------------------------|---------|-------|----------------|-------------|-------------|----------------|------------|-------------|
|                                       |         |       | NO HX DIABETES | HX OBESITY  | HX DIABETES | NO HX DIABETES | HX OBESITY | HX DIABETES |
| <b>Start</b>                          | 0.00%   | 2.32% | 84.17%         | 7.45%       | 4.11%       | 0.19%          | 0.36%      | 1.40%       |
| <b>End</b>                            | 100.00% | 0.00% | 0.00%          | 0.00%       | 0.00%       | 0.00%          | 0.00%      | 0.00%       |
| <b>Not on drug<br/>No hx diabetes</b> | 0.00%   | 2.12% | 97.36%         | 0.35%       | 0.07%       | 0.07%          | 0.02%      | 0.00%       |
| <b>Not on drug<br/>Hx obesity</b>     | 0.00%   | 1.96% | 0.00%          | 96.37%      | 0.22%       | 0.00%          | 1.41%      | 0.03%       |
| <b>Not on drug<br/>Hx diabetes</b>    | 0.00%   | 2.04% | 0.00%          | 0.00%       | 95.47%      | 0.00%          | 0.00%      | 2.49%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 2.13% | 1.67%          | 0.04%       | 0.02%       | 94.20%         | 1.18%      | 0.75%       |
| <b>On drug<br/>Hx obesity</b>         | 0.00%   | 1.86% | 0.00%          | 2.34%       | 0.01%       | 0.00%          | 95.37%     | 0.42%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 1.75% | 0.00%          | 0.00%       | 1.24%       | 0.00%          | 0.00%      | 97.01%      |

**FIGURE 13: HIGH TRANSITION MATRIX (MONTHLY)**

| FROM/TO                               | START   | END   | NOT ON DRUG    | NOT ON DRUG | NOT ON DRUG | ON DRUG        | ON DRUG    | ON DRUG     |
|---------------------------------------|---------|-------|----------------|-------------|-------------|----------------|------------|-------------|
|                                       |         |       | NO HX DIABETES | HX OBESITY  | HX DIABETES | NO HX DIABETES | HX OBESITY | HX DIABETES |
| <b>Start</b>                          | 0.00%   | 2.32% | 84.17%         | 7.45%       | 4.11%       | 0.19%          | 0.36%      | 1.40%       |
| <b>End</b>                            | 100.00% | 0.00% | 0.00%          | 0.00%       | 0.00%       | 0.00%          | 0.00%      | 0.00%       |
| <b>Not on drug<br/>No hx diabetes</b> | 0.00%   | 2.12% | 97.37%         | 0.28%       | 0.06%       | 0.13%          | 0.03%      | 0.00%       |
| <b>Not on drug<br/>Hx obesity</b>     | 0.00%   | 1.96% | 0.00%          | 95.22%      | 0.22%       | 0.00%          | 2.57%      | 0.03%       |
| <b>Not on drug<br/>Hx diabetes</b>    | 0.00%   | 2.04% | 0.00%          | 0.00%       | 95.70%      | 0.00%          | 0.00%      | 2.27%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 2.13% | 1.64%          | 0.03%       | 0.02%       | 95.50%         | 0.42%      | 0.27%       |
| <b>On drug<br/>Hx obesity</b>         | 0.00%   | 1.86% | 0.00%          | 2.43%       | 0.01%       | 0.00%          | 95.50%     | 0.20%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 1.75% | 0.00%          | 0.00%       | 0.25%       | 0.00%          | 0.00%      | 98.00%      |

**FIGURE 14: HIGHEST TRANSITION MATRIX (MONTHLY)**

| FROM/TO                               | START   | END   | NOT ON DRUG    | NOT ON DRUG | NOT ON DRUG | ON DRUG        | ON DRUG    | ON DRUG     |
|---------------------------------------|---------|-------|----------------|-------------|-------------|----------------|------------|-------------|
|                                       |         |       | NO HX DIABETES | HX OBESITY  | HX DIABETES | NO HX DIABETES | HX OBESITY | HX DIABETES |
| <b>Start</b>                          | 0.00%   | 2.32% | 84.17%         | 7.45%       | 4.11%       | 0.19%          | 0.36%      | 1.40%       |
| <b>End</b>                            | 100.00% | 0.00% | 0.00%          | 0.00%       | 0.00%       | 0.00%          | 0.00%      | 0.00%       |
| <b>Not on drug<br/>No hx diabetes</b> | 0.00%   | 2.12% | 97.32%         | 0.31%       | 0.06%       | 0.14%          | 0.04%      | 0.00%       |
| <b>Not on drug<br/>Hx obesity</b>     | 0.00%   | 1.96% | 0.00%          | 94.96%      | 0.22%       | 0.00%          | 2.83%      | 0.03%       |
| <b>Not on drug<br/>Hx diabetes</b>    | 0.00%   | 2.04% | 0.00%          | 0.00%       | 95.47%      | 0.00%          | 0.00%      | 2.49%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 2.13% | 0.74%          | 0.02%       | 0.01%       | 96.36%         | 0.46%      | 0.29%       |
| <b>On drug<br/>Hx obesity</b>         | 0.00%   | 1.86% | 0.00%          | 1.09%       | 0.00%       | 0.00%          | 96.84%     | 0.20%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 1.75% | 0.00%          | 0.00%       | 0.11%       | 0.00%          | 0.00%      | 98.14%      |

**FIGURE 15: RAW 2024 DATA TRANSITION MATRIX (MONTHLY)**

| FROM/TO                               | START   | END   | NOT ON DRUG    | NOT ON DRUG | NOT ON DRUG | ON DRUG        | ON DRUG    | ON DRUG     |
|---------------------------------------|---------|-------|----------------|-------------|-------------|----------------|------------|-------------|
|                                       |         |       | NO HX DIABETES | HX OBESITY  | HX DIABETES | NO HX DIABETES | HX OBESITY | HX DIABETES |
| <b>Start</b>                          | 0.00%   | 2.32% | 84.17%         | 7.45%       | 4.11%       | 0.19%          | 0.36%      | 1.40%       |
| <b>End</b>                            | 100.00% | 0.00% | 0.00%          | 0.00%       | 0.00%       | 0.00%          | 0.00%      | 0.00%       |
| <b>Not on drug<br/>No hx diabetes</b> | 0.00%   | 2.12% | 97.51%         | 0.28%       | 0.06%       | 0.02%          | 0.01%      | 0.00%       |
| <b>Not on drug<br/>Hx obesity</b>     | 0.00%   | 1.96% | 0.00%          | 97.30%      | 0.22%       | 0.00%          | 0.49%      | 0.03%       |
| <b>Not on drug<br/>Hx diabetes</b>    | 0.00%   | 2.04% | 0.00%          | 0.00%       | 95.70%      | 0.00%          | 0.00%      | 2.27%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 2.13% | 8.78%          | 0.18%       | 0.09%       | 85.15%         | 2.24%      | 1.43%       |
| <b>On drug<br/>Hx obesity</b>         | 0.00%   | 1.86% | 0.00%          | 7.70%       | 0.03%       | 0.00%          | 89.78%     | 0.63%       |
| <b>On drug<br/>Hx diabetes</b>        | 0.00%   | 1.75% | 0.00%          | 0.00%       | 5.87%       | 0.00%          | 0.00%      | 92.38%      |

## Limitations and caveats

Our analysis does not include medications fully reimbursed by drug coupons, paid by cash, or otherwise obtained outside of a commercial prescription drug benefit. Similarly, our analysis models market-wide utilization. A given health plan's utilization could certainly differ from the range presented in this paper for a variety of reasons, but particularly if they restrict or expand formulary coverage for certain indications.

To be included in our study, we required that an individual have continuous enrollment for 12 months to establish a history based on medical claims. Any individual enters our start state once this has occurred. As such, our estimates may be more appropriate for more stable commercial populations rather than those with high turnover. It is also possible that our estimates reflect a slightly older population, assuming that younger employees would have higher turnover and be less likely to be included in our study. Unfortunately, this is a limitation of using real-world data.

Milliman does not intend to benefit any third-party recipient of its work product, even if Milliman consents to the release of its work product to such third party. Differences between our projections and actual amounts depend on the extent to which future experience conforms to the assumptions made for this analysis. Actual experience is unlikely to conform exactly to the assumptions used in this analysis. Therefore, actual amounts will almost certainly differ from projected amounts. In performing this analysis, we relied on data and other information provided by the data sources discussed above. We have not audited or verified this data and other information. If the underlying data or information is inaccurate or incomplete, the results of our analysis may likewise be inaccurate or incomplete. We performed a limited review of the data used directly in our analysis for reasonableness and consistency and have not found material defects in the data. If there are material defects in the data, it is possible that they would be uncovered by a detailed, systematic review and comparison of the data to search for data values that are questionable or for relationships that are materially inconsistent. Such a review was beyond the scope of our assignment.

Milliman has developed certain models to estimate the values included in this white paper. The intent of the models was to understand when GLP-1 trends are likely to stabilize for an employer group covering these drugs and to demonstrate the strengths and limitations of using a Markov model to forecast the utilization of GLP-1s. We have reviewed the models, including their inputs, calculations, and outputs, for consistency, reasonableness, and appropriateness to the intended purpose and in compliance with generally accepted actuarial practice and relevant actuarial standards of practice (ASOP).

The models rely on data and information as input to the models. We have relied upon certain data and information provided discussed above for this purpose and accepted it without audit. To the extent that the data and information provided is not accurate or is not complete, the values provided in this white paper may likewise be inaccurate or incomplete. Milliman's data and information reliance includes:

- Enrollment data provided by various sources
- Medical claims data provided by various sources
- Pharmacy claims data provided by various sources
- Wolters Kluwer Medi-Span Master Drug Database v2.5

The models, including all input, calculations, and output, may not be appropriate for any other purpose.

## Solutions for a world at risk™

Milliman leverages deep expertise, actuarial rigor, and advanced technology to develop solutions for a world at risk. We help clients in the public and private sectors navigate urgent, complex challenges—from extreme weather and market volatility to financial insecurity and rising health costs—so they can meet their business, financial, and social objectives. Our solutions encompass insurance, financial services, healthcare, life sciences, and employee benefits. Founded in 1947, Milliman is an independent firm with offices in major cities around the globe.

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