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ARTICLE

Reducing Fraud, Waste, and Abuse Through Real-Time AI-Based Screening: Prospective Results in Deployment

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Fraud, waste, and abuse (FWA) remains a persistent and formidable challenge within the U.S. health care system, reducing affordability and safety while perpetuating health disparities by disproportionately impacting socially vulnerable individuals. This study reports on the prospective results of the deployment of real-time AI-based FWA screening for a large and well-characterized population served by Personify Health, an independent third-party administrator based in Plano, Texas, and serving hundreds of employers in the United States. Between July 1, 2022, and March 31, 2023, incoming claims for 276,833 members were screened for FWA in real time during prepayment using AI-based FWA screening by Health at Scale, a health care machine intelligence company based in San Jose, California. For claims flagged, medical records were requested from billing providers followed by clinical review of the records received and final physician-led adjudication for appropriateness, thus ensuring alignment of medical services and interventions with established guidelines and standards of medical care. Performance was evaluated across the full population and within subgroups including members stratified by social vulnerability. The study found that 3,013 (0.1%) of 2,657,597 claims were flagged in real time by AI-based FWA screening for clinical review. Of those flagged claims, 1,623 (53.9%) were adjudicated for a reduction in the amount paid. The reduction in paid amounts for these claims totaled US$11.8 million (a US$3,914 average reduction per flagged claim and a US$7,267 average reduction per adjudicated reduced claim paid), corresponding to a 1.2% reduction in the total spend for this period (US$11.8 million of US$981.3 million). Compared with members with the lowest social vulnerability (where AI-based FWA screening reduced inappropriate health care reimbursements by 0.9% of overall spend), members with the greatest social vulnerability saw a greater reduction in inappropriate health care reimbursements (1.3%). The results of this study demonstrate that real-time AI-based FWA claims screening for clinical review during prepayment offers potential to reduce inappropriate reimbursements.

Employer-sponsored insurance is the source of health benefits in the United States for 159 million individuals.[1] Over a 5-year period, the average annual premium for employer-sponsored family coverage has increased by 22% (to US$23,968 in 2023 from US$19,616 in 2018) compared with a 27% increase in workers' wages and 21% inflation over that time.[2] This represents an average employee contribution share of US$6,575, up 18.5% from US$5,547, and an employer contribution share of US$17,393, up 23.6% from US$14,069.[2] These increases pose major challenges to both employers, who cover the majority of health benefits expenses, and workers, who are subject to cost sharing through deductibles and co-payments.

Reducing fraud, waste, and abuse (FWA) for employer-sponsored health plans is an imperative need. FWA is a persistent and formidable challenge within the U.S. health care system. The costs of fraud alone are substantial: according to the National Health Care Anti-Fraud Association, an estimated 3% of total health care expenditures are lost to health care fraud.[3] It is estimated that clinical waste further accounts for between 5.4% and 15.7% of health spending, among three categories: failures of care delivery (2.7%–5.7%), failures of care coordination (0.7%–2.1%), and overtreatment (2.0%–8.4%).[4] These costs are significant, considering that employers may transition between preferred provider organization networks in search of 1%–3% expenditure savings. FWA also disproportionately impacts vulnerable populations and perpetuates health disparities.[5] There is a relationship between FWA and health disparities, and vulnerable and underserved individuals are routinely targeted for substandard, medically unnecessary, and harmful care.[5]

Progress in reducing FWA has been limited by traditional approaches — for example, as part of the Fraud Prevention System developed by the U.S. Centers for Medicare & Medicaid Services (CMS)[6] — that rely on screening grounded in rules-based systems and with FWA screening largely restricted to post-payment settings. Traditional systems that rely on manually crafted rules are limited to detecting FWA schemes that are already widely known and obvious. Moreover, these rules fail to factor in clinical nuance,[7] leading to significant false positives that impact real-world usability.[8] The use of such traditional systems is also made challenging by their application to post-payment settings, where recovering inappropriate payments once they have been made is hard, with recovery rates of approximately 18% in "pay-and-chase" post-payment settings.[9,10] The combined effect of these limitations causes many third-party administrators (TPAs) and carriers to curtail their FWA reduction activities to manual high-dollar claim reviews (i.e., requiring all claims above US$100,000 to undergo manual review), ignoring the majority of expenditures and services that take place.

This study reports on the deployment of modern AI-based FWA screening of claims in real time during prepayment for physician-led clinical review. Specifically, the study reports on the prospective results of deployment across a group of employer-sponsored health plans served by an independent TPA and the incremental value of an AI-based approach that offers capabilities beyond existing clearinghouse and claims editing workflows.

> *"The use of such traditional systems is also made challenging by their application to post-payment settings, where recovering inappropriate payments once they have been made is hard, with recovery rates of approximately 18% in 'pay-and-chase' post-payment settings."*

Methods

AI-based FWA screening was deployed for professional (837P file) and institutional (837I file) claims received in X12 electronic data interchange format at Personify Health LLC (formerly Virgin Pulse and HealthComp), a private, independent TPA based in Plano, Texas, that serves several hundreds of employers. Between July 1, 2022, and March 31, 2023, claims at or above a US$4,000 threshold were screened for FWA in real time during prepayment using a commercially available AI-based system (Health at Scale, San Jose, California), developed on a large and representative claims database (including claims for more than 60 million commercially insured members from Merative, formerly IBM Watson Health). The system encoded each member's longitudinal time-indexed sequence of diagnoses (both acute and chronic health conditions), procedures (inclusive of diagnostic and therapeutic services), prescriptions and orders (for drugs, devices, durable medical equipment), and other information relating to care encounters (including categories of providers seen, sites of service, settings of care) to flag claims that were highly irregular and anomalous relative to real-world evidence and care patterns. Lower dollar claims were flagged secondary to high-dollar flagged claims (i.e., if they belonged to the same episode of care as flagged claims at or above the US$4,000 threshold). For any claims flagged in real time, medical records were requested from the billing providers, followed by clinical review of the records by the TPA and final physician-led adjudication of appropriateness, namely looking for inappropriate or unnecessary care, regardless of intent. The review process consisted of a round of review by (at least) one nurse or nurse practitioner, followed by (at least) one physician. The system was applied to screen claims for care already rendered and did not impact any pre-authorization decisions or workflows.

The impact of AI-based FWA screening was prospectively evaluated from initial deployment on July 1, 2022, through March 31, 2023. For flagged claims, reductions in inappropriate payments were measured as the reductions in the dollar amounts paid in the final post-payment record (835 file) issued upon the final adjudicated decision on the claim (i.e., the difference between the amount that was initially expected to have been paid for the 837P or 837I claim after adjusting for network discounts and cost sharing, etc., compared with the actual amount that ended up getting paid per 835). AI-based FWA screening was evaluated across claims categorized by dollar amounts and service types, as well as members subgrouped based on their social vulnerability index (SVI),[11] encompassing multiple variables corresponding to key social determinants of health (SDOH). The Elixhauser Comorbidity Index is being used as a measure of comorbidity burden across different member subsets (all members vs. those with flagged claims), where the comorbidity index is derived based on International Classification of Diseases diagnosis codes.[12]

> *"Members with flagged claims demonstrated patterns of greater utilization of higher-dollar services, with increased age, comorbidity burden, number of claims, and per member per month reimbursements."*

Results

Population Characteristics

Over the 9-month period between July 1, 2022, and March 31, 2023, AI-based FWA screening prospectively analyzed 2,657,597 claims in real time during prepayment from 276,833 members; this represented all claims from all employers in the launch. Table 1 presents the characteristics of the overall study population as well as the group of 1,627 unique members (0.6% of members) for whom 3,013 claims (0.1%) were flagged in real time for clinical review.

Members with flagged claims demonstrated patterns of greater utilization of higher-dollar services, with increased age (47.9 vs. 36.2, $P<0.001$), comorbidity burden (Elixhauser score 8.7 vs. 2.2, $P<0.001$), number of claims (36.1 vs. 9.6, $P<0.001$), and per member per month reimbursements (US$4,585 vs. US$394, $P<0.001$). For members with at least one flagged claim, there was an average of 1.9 claims flagged over the 9-month period.

> *"The greatest reductions in inappropriate spend by AI-based FWA screening were seen for imaging (3.6% reduction in overall spend), cardiovascular procedures (2.5%), and musculoskeletal procedures (2.3%)."*

Prepayment FWA Claims Identification and Payment Reduction

During the study period, 3,013 claims (0.1%) were flagged in real time for clinical review; 54% of these claims (1,623 of 3,013) showed a reduction in paid amounts, with these reductions totaling US$11.8 million (average of US$3,914 reduction per claim flagged). This represented a 1.2% reduction in the total spend of US$981.3 million for the full population over this period.

Claims Categorized by Dollar Amounts

Table 2 presents results across claims categorized by dollar amounts.

The percentage of flagged claims showing a reduction in paid amounts was 42% for claims under US$5,000, with many of these claims flagged secondary to other index higher-dollar claims

Table 1. Study Population Characteristics: Overall Versus Those with Claims Flagged by Real-Time AI-Based FWA Detection, July 1, 2022 to March 31, 2023

Characteristic	Overall Average n=276,833	Flagged Claims Average n=1,627
Age, years	36.2	47.9
Female	57.0%	58.0%
Number of claims	9.6	36.1
Number of claim lines	26.2	124.7
Elixhauser score possible Range: [−2, 133]	2.2	8.7
Elixhauser comorbidities (most common)		
Hypertension	20.5%	42.9%
Obesity	17.5%	28.5%
Depression	9.9%	17.8%
Diabetes	9.8%	20.3%
Chronic lung disease	9.4%	19.1%
Hypothyroidism	8.1%	16.7%
Deficiency anemia	7.9%	23.8%
Liver disease	4.8%	14.2%
Rheumatoid arthritis	3.8%	9.8%
Tumor	2.7%	17.1%
Peripheral vascular disease	3.4%	15.1%
Other thyroid disorders	3.6%	8.9%
Average PMPM Reimbursement	$394	$4,585

PMPM = per member per month. Source: The authors

flagged. For claims above US$5,000, the percentage of flagged claims showing a reduction in paid amounts was relatively consistent (ranging between 56% and 68%). The average reduction in paid amounts per claim flagged increased significantly as the dollar amounts for claims increased, ranging from an average reduction of US$236 for flagged claims under US$5,000 to an average reduction of US$20,513 for those exceeding US$50,000.

Claims Categorized by Service Types

Table 3 presents results for the top 10 service types with the greatest aggregate spend.

Table 2. Claims Flagged by Different Dollar Amounts, July 1, 2022 to March 31, 2023

Claim Dollar Amount Flagged	Number of Claims Flagged in Prepayment	Number of Claims with Any Reductions in Amounts Paid (%)	Number of Claims Denied in Full	Total Reductions in Amounts Paid	Average Reduction Per Claim
<US$5,000	853	356 (42%)	219	US$0.2 million	US$236
US$5,000–9,999	672	407 (61%)	227	US$1.0 million	US$1,504
US$10,000–19,999	633	358 (57%)	199	US$1.6 million	US$2,461
US$20,000–29,999	294	164 (56%)	93	US$1.1 million	US$3,712
US$30,000–39,999	178	105 (59%)	68	US$1.1 million	US$6,161
US$40,000–49,999	101	69 (68%)	46	US$1.1 million	US$10,420
≥$50,000	282	164 (58%)	118	US$5.8 million	US$20,513

Source: The authors

Table 3. Claims Flagged by Type of Service, July 1, 2022 to March 31, 2023

Service Type	Total Number of Claims Filed	Total Spend for Service Type	Number of Claims Flagged in Prepayment	Number of Flagged Claims with Reductions in Amounts Paid (%)	Total Reductions in Amounts Paid on Flagged Claims	Average Reduction Per Claim Flagged	Average Reduction Per Claim Flagged and Reduced	Reduction in Spend for Service Type (%)
Clinic E&M	752,411	US$114.0 million	671	241 (36%)	US$1.7 million	US$2,527	US$7,036	1.5%
Inpatient E&M	44,379	US$84.8 million	106	52 (49%)	US$0.5 million	US$4,963	US$10,118	0.6%
Emergency E&M	72,319	US$78.4 million	275	161 (59%)	US$1.1 million	US$3,949	US$6,746	1.4%
Digestive	25,229	US$53.4 million	185	118 (64%)	US$0.5 million	US$2,902	US$4,550	1.0%
Musculoskeletal	17,806	US$52.5 million	124	83 (67%)	US$1.2 million	US$9604	US$14,348	2.3%
Imaging	131,164	US$40.3 million	309	195 (63%)	US$1.4 million	US$4,666	US$7,394	3.6%
OB/GYN	11,165	US$39.4 million	11	7 (64%)	<US$0.1 million	US$2,162	US$3,397	0.1%
Drug injections	12,599	US$38.7 million	175	109 (62%)	US$0.6 million	US$3,252	US$5,222	1.5%
Critical care	6,320	US$25.0 million	24	14 (58%)	US$0.2 million	US$10,332	US$17,711	1.0%
Cardiovascular	27,788	US$24.4 million	58	40 (69%)	US$0.6 million	US$10,332	US$14,981	2.5%

Note: The type of service designation is determined with each claim assigned to a service type based on the claim line with the highest dollar amount. This table presents the top 10 services by total spend. E&M = evaluation and management, OB/GYN = obstetrics and gynecology. Source: The authors

The total reimbursements for these 10 service types was US$550.9 million (56% of overall spend). Collectively, there were 1,938 flagged claims for these services (64% of all flagged claims). The percentage of flagged claims showing a reduction in paid amounts ranged from 36% for clinic care (aggregating evaluation and management services for primary and specialist care performed in outpatient clinic settings) to 69% for cardiovascular procedures. The greatest reductions in inappropriate spend by AI-based FWA screening were seen for imaging (3.6% reduction in overall spend), cardiovascular procedures (2.5%), and musculoskeletal procedures (2.3%). The greatest average reductions in paid amounts per flagged claim were observed for cardiovascular procedures (US$10,332 reduction on average per flagged claim), critical care services (US$10,332), and musculoskeletal procedures (US$9,604).

> *“Most systems to target FWA fall into the trap of pay-and-chase rather than identifying risks and resolving difficulties before they arise.”*

Equity Considerations

The results of AI-based FWA screening for members in zip codes associated with various bands of social vulnerability, and unknown social vulnerability, are presented in Table 4.

Compared with members who live in communities where the social vulnerability is in the lowest quartile, (where AI-based FWA screening reduced inappropriate reimbursements in aggregate by 0.9% of total spend), members with greatest social vulnerability (in the quartile with the highest SVI score) saw greater reduction in inappropriate health care reimbursements (1.3%). This increase was greater still (2.0%) for the 53 members with unknown social vulnerability. These results were consistent with the average reduction in paid amounts per flagged claim, which ranged

Table 4. Claims Flagged by Social Vulnerability Index Corresponding to Member's Zip Code

Social Vulnerability Index of Member Zip Code	Total Number of Members (%)	Number of Claims Flagged in Prepayment	Number of Flagged Claims with Reductions in Amounts Paid (%)	Total Reductions in Amounts Paid on Flagged Claims	Average Reduction Per Claim Flagged	Total Spend for Subgroup	Reduction in Spend for Subgroup (%)*
Low vulnerability (0.0–0.2500)	44,422 (16.0%)	453	213 (47%)	US$1.4 million	US$3,035	US$155.4 million	0.9%
Low–medium vulnerability (0.2501–0.50)	73,043 (26.39%)	759	438 (58%)	US$3.0 million	US$3,916	US$263.3 million	1.1%
Medium–high vulnerability (0.5001–0.7500)	67,071 (24.23%)	769	424 (55%)	US$3.2 million	US$4,118	US$246.9 million	1.3%
High vulnerability (0.7501–1.0)	86,597 (31.28%)	979	512 (52%)	US$3.9 million	US$3,973	US$296.3 million	1.3%
Unknown	5,700 (2.06%)	53	36 (68%)	US$0.4 million	US$7,381	US$19.4 million	2.0%

Note: The social vulnerability index is measured on a scale between 0 and 1, where 1 indicates the greatest vulnerability. *The rate of reduction in the claims belonging to the high vulnerability group (0.7501–1) is found to be larger than that of the low vulnerability group (0–0.25) using a Mann–Whitney *U* test (5% significance level). Source: The authors

from US$3,035 (lowest quartile for social vulnerability) to US$3,973 (highest quartile for social vulnerability) to US$7,381 (unknown social vulnerability).

Discussion

Despite the importance of FWA as a public health challenge, limited progress has been made in targeting this problem. Estimates of the rate of FWA remain in the double-digits, as much as 25%.[4,13] Most systems to target FWA fall into the trap of pay-and-chase rather than identifying risks and resolving difficulties before they arise.[14] This is compounded by systems for FWA detection being historically grounded in manually crafted rules, which require FWA schemes to be known ahead of time (and are therefore slow to catch up with evolving patterns of FWA) and further fail to factor in clinical nuance leading to substantial false positives and limiting real-world practical use.

> *"The ability to cover claims below US$100,000 and achieve a consistently high rate of efficiency ... offers the potential to bring a fuller set of reimbursements into the realm of FWA screening, beyond traditional high-dollar reviews that consider only a small fraction of overall spend and services."*

Advances in AI offer significant potential for data-driven FWA screening that factors in deep historical context about patients, providers, and patterns of care, and can be implemented in real time during claim prepayment (i.e., ahead of inappropriate health care reimbursements). In this study, AI-based FWA screening achieved a 1.2% reduction in overall reimbursement with an average US$3,914 reduction in paid amounts per claim flagged. Only a small subset (0.1%) of all claims was flagged over this period. Over 54% of these claims showed a reduction in paid amounts. It is worth noting that the remaining 46% of flagged claims without a reduction in paid amounts should not be considered non-FWA; rather, these cases included situations where the underlying contracts between the insurers and providers limited the ability to request records or pursue actions, or where a determination was made to pursue action post payment upon observing recurrence of the activity across subsequent claims.

The results of this study were achieved in practical real-world settings over and above existing clearinghouse and claims editing upstream of AI-based FWA screening, establishing substantial incremental impact beyond these workflows. The impact of AI-based FWA screening was consistent across service types and claims of different dollar amounts, including claims outside traditional high-dollar manual claim review workflows. The ability to cover claims below US$100,000 and achieve a consistently high rate of efficiency (by reducing the need for manual review or targeting to identify inappropriate claims) offers the potential to bring a fuller set of reimbursements into the realm of FWA screening, beyond traditional high-dollar reviews that consider only a small fraction of overall spend and services. In total, the results of this launch showed the ability of AI-based FWA screening to achieve an additional US$11.8 million in savings, significantly exceeding the cost of service and delivering a sevenfold return on investment.

AI-based FWA screening also showed a substantially greater reduction in inappropriate reimbursements for members in the highest quartile of social vulnerability (1.3% of overall spend) than for members in the lowest quartile (0.9%). Individuals whose SDOH lead to health disparities are disproportionately vulnerable to FWA and less able to mitigate harm caused by inappropriate care.[15] For example, a 2019 study conducted by Johns Hopkins University found that providers banned from Medicare due to FWA had been treating patients who were more likely to be minorities, disabled, or dually enrolled in Medicaid.[16]

In performing this study, AI-based FWA screening was applied to claims exceeding a dollar threshold of US$4,000. There is significant FWA in claims below this threshold, especially for health care services that are low value but high volume,[17] and further investigations should evaluate the potential to target such FWA. More research is also warranted to evaluate the potential of AI-based FWA screening in other insured groups, including Medicare, Medicaid, and fully insured commercial populations. It is reasonable to expect that AI-based FWA screening may offer significant opportunity within these groups. More research is needed to fully quantify this impact.

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