

OMOP Insights: Standardizing the First Combat Trauma Registry

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Background

The Joint Trauma System (JTS) is the Trauma Center of Excellence for the Military Health System (MHS), improving trauma outcomes through evidence-based performance improvement. The JTS relies on high-quality data from the Department of Defense Trauma Registry (DODTR), the most comprehensive combat trauma registry in the world with 95,000 patients, 149,000 records, and over 400 publications.[1, 2] Data-driven analyses such as the Golden Hour policy decreased case fatality rates from 13.7% to 7.6%.[3]

Despite its richness, the DODTR has operational constraints. Its workflow relies on 100% manual abstraction, with abstractors completing two to three cases per day and spending 50–75% of time locating and curating records from heterogeneous sources.[4] Source attribution is lost during manual abstraction, challenging data provenance and trustworthiness. A complex table structure limits consistent querying, and proprietary contracts restrict rapid addition of new data elements.

To address these limitations, JTS developed the System for Injury Monitoring and Outcomes Nexus (SIMON) (Figure 1). SIMON utilizes the Observational Medical Outcomes Partnership (OMOP) Common Data Model (CDM), providing a fixed, standard structure for consistent meaning, mapping, and relationships across multiple data sources.[5] SIMON aims to harmonize operational combat data with National Trauma Database (NTDB) and American College of Surgeons (ACS) standards.[6] Other institutions have used OMOP to address data quality and analytical consistency challenges.[7] We aim to demonstrate OMOP can normalize combat trauma data into a unified, reliable representation.

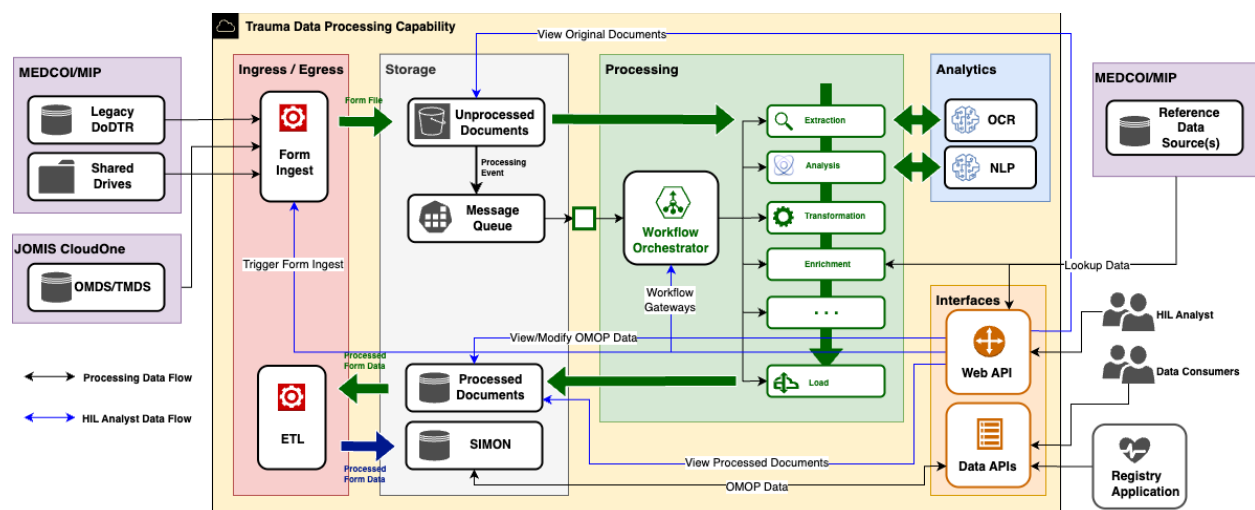


Figure 1 (modified from Remondelli et al., 2025).[8] SIMON automatically ingests health record data from multiple sources including the Operational Medicine Data Store (OMDS) and Theater Medical Data Store (TMDS). Tools for optical character recognition and natural language processing identify form types and valid data elements with human-in-the-loop review. All annotations are reconciled and processed into the OMOP structure via a web-based graphical user interface.

Methods

A team of 6 clinicians, informaticists, and data scientists performed manual review of all tables, fields, and OMOP concept ID mappings over 18 months totaling 200 work hours. A two-layer system using Oracle and SQL transforms DODTR source data into the OMOP standard. The initial layer applies business rules to reformat source data; the second layer enriches data with OMOP concept IDs. Data is validated against standard Quality Assurance (QA) metrics. Once validated, an Extract-Transform-Load (ETL) process migrates data into a Microsoft SQL Server environment (SIMON), passing through a landing zone and staging area where primary and foreign keys establish data relationships before reaching production. We used Oracle 19c, Toad for Oracle, DBeaver 22.2.0, and SQL Server 2019.

Results

TOTAL	100	100	498	2,482,282	2	4,195	100%	100%
Bloods/Fluids	4.8	1.04	24	25,966	0	0	100%	100%
Demographic	10	39.5	50	982,106	0	0	100%	100%
Discharge	17.2	4.01	86	99,611	0	0	100%	100%
Dx	13.4	6.89	67	171,344	0	0	100%	100%
ED	20	10.22	98	249,833	2	4,195	98%	98%
Memo	2.8	36.2	14	900,023	0	0	100%	100%
NTDB/TQIP	14.2	0.34	71	8,474	0	0	100%	100%
PI	1	0.18	5	4,510	0	0	100%	100%
Procedures	7.6	11.76	38	292,325	0	0	100%	100%
Provider/Consult	0.6	0.31	3	7,652	0	0	100%	100%
Pt Tracking	2.2	3.97	11	98,655	0	0	100%	100%
Arrival Transport	22	8.48	110	210,749	0	0	100%	100%
Injury	11.4	3.61	57	89,797	0	0	100%	100%

Table 1: DODTR Source vs OMOP Mapped Data

A comparison between DODTR source data and OMOP mapped data shows 98.2% correspondence (Table 1), with the remaining 1.8% attributed to provider table missingness. Patient demographics, injury type, role of care, and military operation counts were identical between DODTR and OMOP, confirming no data loss during conversion.

	Verification				Validation				Total			
	Pass	Fail	Total	% Pass	Pass	Fail	Total	% Pass	Pass	Fail	Total	% Pass
Plausibility	453	77	526	86%	287	4	291	99%	740	81	817	91%
Conformance	953	52	995	96%	180	8	180	100%	1133	60	1175	96%
Completeness	514	10	524	98%	15	2	17	88%	529	12	541	98%
Total	1920	139	2045	94%	482	14	488	99%	2402	153	2533	95%

Figure 2: OMOP Quality Assurance (QA) Dashboard

The OMOP QA dashboard (Figure 2) showed a 95% overall score across plausibility, conformance, and completeness. The remaining 5% reflected missing dates/times, non-standard mappings, and domain mismatches.

To validate clinical accuracy beyond structural adherence, three cohorts from the Damage Control Resuscitation (DCR) Clinical Practice Guideline were compared (Figure 3). Total concordance was observed between DODTR and OMOP across all three populations, confirming identical results regardless of which dataset is queried.

DCR CPG Comparison: DODTR Vs OMOP		DCR 1					
Category	Measure/Level	DODTR			OMOP		
		Active Duty	Non-US Military	Other	Active Duty	Non-US Military	Other
Age (years)	Mean	26	27	28	26	27	28
	Median	24	25	25	24	25	25
Injury Classification	Battle	4638	5098	9196	4638	5098	9196
	Non-Battle	736	451	1951	736	451	1951
	Other	0	38	248	0	38	248
First Role of Care (Visit)	Role 1 (Point of Injury)	196	87	241	196	87	241
	Role 2 (Resuscitative care)	1613	1904	3619	1613	1904	3619
	Role 3 (Theater Hospital)	3268	3584	7041	3268	3584	7041
Fluids >=1L PH	Y	215	106	187	216	106	187
Fluids >=2L	Y	3527	4136	6964	3530	4124	6964
Injury Type	Blunt	2743	1523	2961	2743	1523	2961
	Burn	404	291	700	404	291	700
	Other	67	18	44	67	18	44
	Penetrating	3905	4921	9346	3905	4921	9346
Military Operation	Freedom's Sentinel	111	404	420	111	404	420
	Inherent Resolve	54	223	850	54	223	850
	New Dawn	32	16	59	32	16	59
	OEF	2145	3000	4933	2145	3000	4933
	OIF	2799	1900	4639	2799	1900	4639
Race	Other	233	44	494	233	44	494
	American Indian	21	0	2	21	0	2
	Asian	51	101	333	51	101	333
	Black or African American	363	28	101	363	28	101
	Native Hawaiian	55	2	65	55	2	65
	Other	1492	3254	6176	1492	3254	6176
	White	3392	2202	4718	3392	2202	4718
Received WB	Y	720	498	1199	720	498	1199
Received WB or Cryo	Y	1604	1422	2380	1604	1422	2380
Received WB or PLT	Y	2054	1919	3285	2054	1919	3285
Sex	Female	142	12	1270	142	12	1270
	Male	5232	5572	10107	5232	5572	10107
	Other	0	3	18	0	3	18
TXA MTF	Y	314	392	773	314	392	773
TXA PH	Y	115	214	268	115	214	268
Total		42,291	43,415	84,641	42,295	43,403	84,641

Table 2: Benefits and Challenges of OMOP Implementation

SIMON provides several benefits (Table 2): centralized data harmonization, uniform aggregation of clinical domains through long-table architecture, improved source attribution, automated cohort

capture through well-defined business rules, and machine-readable datasets for AI/ML applications. NATO partners and other users can select cohorts of interest and obtain consistent results.

Challenges included OMOP's strict conventions requiring iterative design to accommodate complex data types and missingness. Patient movement records frequently lacked dates and times, necessitating inheritance and imputation rules. Over 4,000 custom mappings were created for JTS-specific concepts not represented in standard OMOP vocabularies, impacting the overall quality score. A central person index remains housed outside the OMOP structure.

Limitations

Imputation for medications and procedures used encounter or visit detail entry/exit times. The DODTR does not currently capture devices; the fact_relationship table will incorporate these in future iterations.

Conclusion

Our study demonstrates a structurally reliable and semantically valid approach to mapping the first combat registry into the OMOP CDM. No data was lost during conversion, confirming ETL trustworthiness and scalability for future conflicts. The OHDSI community should recognize the feasibility of applying OMOP to operational military trauma registries and consider this framework as a model for harmonizing complex, heterogeneous clinical data across diverse healthcare settings.

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