

Supplementary Information

Blind Spots in AI-Assisted Healthcare Evidence Search: Multiplatform Evaluation of Clinical Retrieval Gaps and Risk-of-Bias

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Table of Contents

Section	Title	Page
Part 1. Search Strategy and Gold Standard		
Checklist	PRISMA-ScR reporting checklist	3–5
Table S1	Detailed search strategy	6–35
Table S2	Gold-standard references (N = 83)	36–47
Part 2. Citation Matching and Threshold Selection		
Table S3	Overlap-band sweep establishing the 40% operational matching threshold (20–60% Jaccard overlap)	47–48
Figure S1	Empirical determination of the title-overlap matching threshold	48
Supplementary Data 1	Candidate-level matching dataset	Separate file
Part 3. Platform Retrieval Performance		
Table S5	Experimental design summary and inference units	49–50
Table S6	Complete performance metrics for all 75 platform–strategy–variation combinations, ranked by F1-score	50–53
Table S7	Pairwise comparisons of platform-level pooled recall	53–54
Table S8	Ai2 Finder recall before and after the 100-result output cap	54
Table S9	Per-formulation Ai2 Finder recall, full vs capped output	54–55
Table S10	Platform summary: formulation-level and pooled recall, with precision and consistency distributions	55–56
Table S11	Median formulation-level recall by prompting strategy	56
Table S12	Strategy-level performance summary across platforms	56–57
Part 4. Prompting Framework		
Table S13	Formulation design principles	57–58
Table S14	Core concepts explored by prompting strategy and variation	58–59
Table S15	Verbatim prompt texts with design rationale	59–67
Table S16	Concurrent modifications and interpretation framework	68
Part 5. Cross-Platform Coverage and Complementarity		
Table S17	Unique and shared study contributions by platform	69
Table S18	Greedy sequential combination strategy	69–70
Table S19	All 10 pairwise platform combinations ranked by union recall	70
Part 6. Retrieval Patterns by Evidence Domain and Publication Characteristics		
Table S20	Single-query zero-retrieval probability per platform, by evidence domain	70–71
Table S21	Publisher-level retrieval analysis (ordered by retrieval tier)	71–72
Table S22	Platform-level retrieval by substance domain	72
Table S23	Retrieval by NLP methodology	72–73
Table S24	Retrieval by publication year	73–74
Figure S2	Study-level retrieval by publication period	74
Part 7. Never-Retrieved and Difficult-to-Retrieve Studies		
Table S25	Complete list of never-retrieved studies (n = 10)	74–75
Table S26	Convergent characteristics of never-retrieved studies	75
Table S27	Platform-specific non-retrieval summary	76
Table S28	Platform-specific unique failures	76
Table S29	Never-retrieved studies by platform	76–77
Part 8. References		78

Supplementary Information

PART 1. Search Strategy and Gold Standard

Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	Reported in the present submission
TITLE			
Title	1	Identify the report as a scoping review.	Not applicable to the article title because the present manuscript is a retrieval-evaluation study, not a scoping-review report. The scoping-review component is identified in Methods: Gold Standard Development as the PRISMA-ScR-guided process used to construct the gold-standard corpus.
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	The Abstract identifies the use of a prospectively assembled, PRISMA-guided gold-standard corpus and reports how it was used for retrieval evaluation. Detailed corpus-construction methods are provided in Methods: Gold Standard Development and the Supplementary Information.
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	Introduction explains the need for prospectively assembled, non-public gold-standard benchmarks for evaluating retrieval performance. Methods: Gold Standard Development explains why the selected evidence domain was suitable for stress-testing retrieval because of evolving terminology, methodological diversity, and dispersed publication venues.
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	Methods: Gold Standard Development states that the corpus was developed to assess whether platforms could surface individually published eligible studies in response to realistic queries, rather than reproduce a known reference set. The healthcare evidence question concerned NLP tools developed and tested for identifying substance use or substance use disorders from unstructured clinical text in EHRs.
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	Reporting followed PRISMA-ScR guidance. No publicly registered protocol was used for the corpus-construction component.
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	Methods: Gold Standard Development reports that included studies were peer-reviewed original research, published in English, reporting quantitative performance metrics for computational methods identifying substance use or substance use disorders from unstructured clinical text in human populations. Additional details are provided in the Supplementary Information.

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	Reported in the present submission
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	Methods: Gold Standard Development reports that a health sciences librarian and domain experts developed comprehensive search strategies across seven biomedical, multidisciplinary, and computer science databases. The complete search strategy is provided in Table S1 .
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	Table S1 provides the complete search strategy used to assemble the gold-standard corpus.
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	Methods: Gold Standard Development reports that, after deduplication, two independent reviewers screened citations at title/abstract and full-text stages using Covidence, with discrepancies resolved by third-reviewer arbitration.
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	Data charting consisted of extracting the study-level variables needed to define and characterize the gold-standard corpus, including bibliographic details, substance category, publication characteristics, venue type, and other variables used in the retrieval-gap analyses (Table S2 and Supplementary Information).
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	Table S2 lists the prospectively assembled gold-standard corpus. The present manuscript and Supplementary Information use study-level variables including substance category, publication year, venue type, journal/conference source, publisher, and retrieval status across platforms.
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	Not performed. Critical appraisal was not required for the purpose of constructing a retrieval benchmark and is optional for scoping reviews. The corpus was used to evaluate retrieval coverage, not to synthesize clinical effectiveness or estimate pooled effects.
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	Methods: Gold Standard Development, Performance Analysis, and Statistical Analysis describe how the charted corpus was used as the benchmark for recall, precision, single-query zero-retrieval probability, publication-year analyses, venue-type analyses, and cross-platform coverage/complementarity analyses.
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	Methods: Gold Standard Development reports that the search yielded 4,624 citations, which two independent reviewers screened in Covidence (with third-reviewer arbitration) to a final PRISMA-ScR-guided gold standard of 83 studies. A separate PRISMA-ScR flow diagram is not included, consistent with use of the corpus as a retrieval benchmark rather than as a stand-alone review.

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	Reported in the present submission
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	Table S2 provides the included-study list and study-level characteristics for the 83-study gold-standard corpus.
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	Not applicable. Critical appraisal was not performed.
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	Table S2 and the retrieval-output supplementary tables present study-level corpus information and per-study retrieval outcomes used in the evaluation.
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	Results and the Supplementary Information summarize retrieval across the charted evidence corpus by platform, substance category, publication year, venue type, publisher/journal hierarchy, and cross-platform complementarity.
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	Discussion summarizes how the PRISMA-ScR-guided corpus revealed incomplete and uneven AI-assisted retrieval, with implications for clinicians, researchers, and platform developers.
Limitations	20	Discuss the limitations of the scoping review process.	Discussion notes that the study evaluated one research question and evidence corpus, and that retrieval performance may differ across clinical topics, languages, publication ecosystems, access conditions, and time periods.
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	Discussion interprets the corpus as a transparent benchmark for assessing retrieval coverage, stability, and blind spots, and states that the framework can be extended across clinical topics.
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	Acknowledgements reports that no funding was received for this research.

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Ann Intern Med. 2018 Oct 2;169(7):467-473. doi:10.7326/M18-0850

Table S1. Detailed Search Strategy

Database	Search Strategy
PubMed	#1 "Analgesics, Opioid"[Pharmacological Action] OR "Analgesics, Opioid"[Mesh] OR algopan[tiab] OR biopon[tiab] OR laudanum[tiab] OR nepenthe[tiab] OR omnopon[tiab] OR opial[tiab] OR opiate*[tiab] OR "opiate alkaloid"[tiab] OR "opiate alkaloids"[tiab] OR opioid*[tiab] OR opium[tiab] OR "opium alkaloid"[tiab] OR "opium alkaloids"[tiab] OR "opium derivative"[tiab] OR "opium poppy"[tiab] OR "opium tincture"[tiab] OR opon[tiab] OR pantopon[tiab] OR papaveretum[tiab] OR pavon[tiab] OR tetrapon[tiab] #2 "Heroin"[Mesh] OR acetomorphine[tiab] OR "diacetyl morphine"[tiab] OR diacetylmorphine[tiab] OR "diacetylmorphine hydrochloride"[tiab] OR diamorphine[tiab] OR "diamorphine hydrochloride"[tiab] OR diaphorin[tiab] OR heroin[tiab] OR "heroin hydrochloride"[tiab] OR heroine[tiab] OR morphacetin[tiab] #3 "Oxycodone"[Mesh] OR alivio[tiab] OR bionone[tiab] OR "col 003"[tiab] OR col003[tiab] OR dihydrohydroxycodone[tiab] OR dihydron[tiab] OR endone[tiab] OR eubine[tiab] OR eucodal[tiab] OR eucodolum[tiab] OR eukodal[tiab] OR nargenol[tiab] OR "nsc 19043"[tiab] OR opton[tiab] OR ossicodone[tiab] OR oxanest[tiab] OR oxaydo[tiab] OR oxecta[tiab] OR oxiconona[tiab] OR oxicone[tiab] OR "oxy ir"[tiab] OR oxycodon[tiab] OR oxycodone[tiab] OR "oxycodone hcl"[tiab] OR "oxycodone hydrochloride"[tiab] OR oxycone[tiab] OR oxycontin[tiab] OR "oxycontin neo"[tiab] OR oxydol[tiab] OR oxyfast[tiab] OR oxygesic[tiab] OR oxyir[tiab] OR oxylan[tiab] OR oxyneo[tiab] OR oxynorm[tiab] OR oxypro[tiab] OR pavinal[tiab] OR pronarcin[tiab] OR "pti 821"[tiab] OR pti821[tiab] OR remoxy[tiab] OR roxicodone[tiab] OR roxybond[tiab] OR xtampza[tiab] OR "xtampza er"[tiab] #4 "Hydrocodone"[Mesh] OR bekadid[tiab] OR dico[tiab] OR dicodid[tiab] OR dihydrocodeinone[tiab] OR hydrocodone[tiab] OR hydrocodonum[tiab] #5 "Fentanyl"[Mesh] OR "ap 48"[tiab] OR ap48[tiab] OR "az 003"[tiab] OR az003[tiab] OR duragesic[tiab] OR "duragesic-100"[tiab] OR "duragesic-12"[tiab] OR "duragesic-25"[tiab] OR "duragesic-50"[tiab] OR "duragesic-75"[tiab] OR durogesic[tiab] OR durotep[tiab] OR fentamyl[tiab] OR fentanil[tiab] OR fentanyl[tiab] OR "fentanyl buccal soluble film"[tiab] OR "fentanyl hydrochloride"[tiab] OR "fentanyl iontophoretic"[tiab] OR "fentanyl-100"[tiab] OR "fentanyl-12"[tiab] OR "fentanyl-25"[tiab] OR "fentanyl-37"[tiab] OR "fentanyl-50"[tiab] OR "fentanyl-75"[tiab] OR jns020qd[tiab] OR leptanal[tiab] OR matrifin[tiab] OR pecfent[tiab] OR phentanyl[tiab] OR "r 4263"[tiab] OR r4263[tiab] OR recuvyra[tiab] OR subsys[tiab] OR tanyl[tiab] #6 "Morphine"[Mesh] OR anpec[tiab] OR duromorph[tiab] OR epimorph[tiab] OR miro[tiab] OR morfin[tiab] OR morfina[tiab] OR morphia[tiab] OR morphin[tiab] OR morphine[tiab] OR "morphine alkaloid"[tiab] OR "morphine chlorhydrate"[tiab] OR "morphine chloride"[tiab] OR "morphine hydrochloride"[tiab] OR "morphine suspension"[tiab] OR morphinium[tiab] OR morphium[tiab] OR opso[tiab] OR skenan[tiab] OR "trans morphine"[tiab] #7 "Codeine"[Mesh] OR codein[tiab] OR codeine[tiab] OR codipertussin[tiab] OR codyl[tiab] OR "methyl morphine"[tiab] OR methylmorphine[tiab] OR "morphine 3 methyl ether"[tiab] OR "morphine monomethyl ether"[tiab] OR "trans codeine"[tiab]

#8

"Methadone"[Mesh] OR adanon[tiab] OR algolysin[tiab] OR algovetin[tiab] OR amidon[tiab] OR amidone[tiab] OR "an 148"[tiab] OR an148[tiab] OR anadon[tiab] OR butalgin[tiab] OR deamin[tiab] OR deipridol[tiab] OR diaminon[tiab] OR dolamid[tiab] OR dolmed[tiab] OR dolophin[tiab] OR dolophine[tiab] OR dorex[tiab] OR eptadone[tiab] OR fenadon[tiab] OR heptadon[tiab] OR heptadone[tiab] OR heptanon[tiab] OR ketalgin[tiab] OR "l-polamidon"[tiab] OR mecodin[tiab] OR metadol[tiab] OR metadon[tiab] OR methaddict[tiab] OR methadon[tiab] OR methadone[tiab] OR "methadone base"[tiab] OR "methadone hydrochloride"[tiab] OR methadose[tiab] OR miadone[tiab] OR phenadon[tiab] OR physeptone[tiab] OR polamidon[tiab] OR polamivet[tiab] OR "sedo-rapide"[tiab] OR symoron[tiab] OR win[tiab]

#9

"Buprenorphine"[Mesh] OR addnok[tiab] OR astec[tiab] OR belbuca[tiab] OR brixadi[tiab] OR buprenex[tiab] OR buprenorfin[tiab] OR buprenorfina[tiab] OR buprenorfine[tiab] OR buprenorphin[tiab] OR buprenorphine[tiab] OR "buprenorphine hydrochloride"[tiab] OR butec[tiab] OR butrans[tiab] OR buvidal[tiab] OR cam2038[tiab] OR lepetan[tiab] OR "lyn 013"[tiab] OR lyn013[tiab] OR norphin[tiab] OR norspan[tiab] OR probuphenine[tiab] OR probuphine[tiab] OR "rbp 6000"[tiab] OR rbp6000[tiab] OR sixmo[tiab] OR sublocade[tiab] OR subutex[tiab] OR temgesic[tiab] OR transtec[tiab]

#10

"Tramadol"[Mesh] OR ad2112[tiab] OR adamon[tiab] OR adolonta[tiab] OR amanda[tiab] OR analab[tiab] OR andalpha[tiab] OR bio301[tiab] OR calmol[tiab] OR "cg 315"[tiab] OR "cg 315e"[tiab] OR cg315[tiab] OR contramal[tiab] OR conzip[tiab] OR dolzam[tiab] OR "e 382"[tiab] OR e381[tiab] OR e382[tiab] OR marol[tiab] OR monocriox[tiab] OR noax[tiab] OR nobligan[tiab] OR "ns 24"[tiab] OR ns24[tiab] OR prontalgin[tiab] OR qdolo[tiab] OR ralivia[tiab] OR ryzolt[tiab] OR "t-long"[tiab] OR tioner[tiab] OR tiparol[tiab] OR topalgic[tiab] OR "topalgic lp"[tiab] OR toram[tiab] OR tradolan[tiab] OR tradonal[tiab] OR tralgit[tiab] OR tramadol[tiab] OR "tramadol hcl"[tiab] OR "tramadol hydrochloride"[tiab] OR "tramadol lp"[tiab] OR "tramadol retard"[tiab] OR "tramadol sr"[tiab] OR tramadolis[tiab] OR tramadolo[tiab] OR tramador[tiab] OR tramal[tiab] OR tramazac[tiab] OR tramol[tiab] OR tramundin[tiab] OR tridol[tiab] OR tridural[tiab] OR trodon[tiab] OR ultram[tiab] OR "ultram er"[tiab] OR zamadol[tiab] OR zertane[tiab] OR zydol[tiab] OR "zydol sr"[tiab] OR zytram[tiab]

#11

"Hydromorphone"[Mesh] OR dihydromorphinone[tiab] OR dihydromorphone[tiab] OR dilaudid[tiab] OR dimorphone[tiab] OR exalgo[tiab] OR "hydromorph contin"[tiab] OR hydromorphon[tiab] OR hydromorphone[tiab] OR "hydromorphone hydrochloride"[tiab] OR jurnista[tiab] OR novolaudon[tiab] OR palladon[tiab] OR palladone[tiab]

#12

"Oxymorphone"[Mesh] OR hydroxydihydromorphinone[tiab] OR numorphan[tiab] OR opana[tiab] OR "opana er"[tiab] OR oxymorphone[tiab] OR "oxymorphone hydrochloride"[tiab]

#13

"Cannabinoids"[Mesh] OR "Cannabis"[Mesh] OR cannabinoid[tiab] OR cannabinoids[tiab] OR "cannabis sativa extract"[tiab] OR "cannabis sativa resin"[tiab] OR bhang[tiab] OR cannabis[tiab] OR "cannabis constituent"[tiab] OR "cannabis extract"[tiab] OR "cannabis leaf"[tiab] OR cannador[tiab] OR charas[tiab] OR ganja[tiab] OR hashish[tiab] OR "hashish oil"[tiab] OR "hemp extract"[tiab] OR marihuana[tiab] OR marijuana[tiab] OR "Medical Marijuana"[Mesh] OR "medical cannabis"[tiab] OR "medical marihuana"[tiab] OR "medical marijuana"[tiab] OR "medicinal cannabis"[tiab] OR "medicinal marijuana"[tiab] OR "marijuana treatment"[tiab] OR "Dronabinol"[Mesh] OR "1 trans delta 9 tetrahydrocannabinol"[tiab] OR "delta 1 tetrahydrocannabinol"[tiab] OR "delta 1 trans tetrahydrocannabinol"[tiab] OR "delta 9 tetrahydrocannabinol"[tiab] OR "delta 9 trans tetrahydrocannabinol"[tiab] OR "delta1 tetrahydrocannabinol"[tiab] OR "delta1 the"[tiab] OR "delta1 trans tetrahydrocannabinol"[tiab] OR "delta9 tetrahydro cannabinol"[tiab] OR "delta9 tetrahydrocannabinol"[tiab] OR "delta9 trans tetrahydrocannabinol"[tiab] OR dronabinol[tiab] OR "l delta 9 trans tetrahydrocannabinol"[tiab] OR marinol[tiab] OR "qcd 84924"[tiab] OR

syndros[tiab] OR "tetrahydrocannabinol delta9"[tiab] OR "trans delta 9 tetrahydrocannabinol"[tiab] OR thc[tiab] OR "delta 3 tetrahydrocannabinol"[tiab] OR "delta tetrahydrocannabinol"[tiab] OR "delta3 tetrahydrocannabinol"[tiab] OR "sp 104"[tiab] OR "tetrahydrocannabinol"[tiab] OR tetrahydrocannabinol[tiab] OR tetrahydrocannabinol[tiab] OR tetrahydrocannabinol[tiab] OR "trans tetrahydrocannabinol"[tiab] OR scb[tiab]

#14

"Ethanol"[Mesh] OR alcohol[tiab] OR ethanol[tiab] OR ethylalcohol[tiab]

#15

"Alcoholic Beverages"[Mesh] OR "Absinthe"[Mesh] OR "Beer"[Mesh] OR "Wine"[Mesh] OR "alcoholic beverage"[tiab] OR "alcoholic beverages"[tiab] OR "alcoholic drink"[tiab] OR "liquor alcohol"[tiab] OR absinthe[tiab] OR beer[tiab] OR brandy[tiab] OR gin[tiab] OR makgeolli[tiab] OR makkoli[tiab] OR makoli[tiab] OR "honey wine"[tiab] OR pulque[tiab] OR rum[tiab] OR "rice wine"[tiab] OR sake[tiab] OR vodka[tiab] OR bourbon[tiab] OR "bourbon whiskey"[tiab] OR "scotch whiskey"[tiab] OR whiskey[tiab] OR whisky[tiab] OR wine[tiab] OR "apple cider"[tiab] OR "apple wine"[tiab] OR cider[tiab]

#16

"Benzodiazepines"[Mesh] OR benzodiazepine[tiab] OR benzodiazepines[tiab]

#17

"Phenobarbital"[Mesh] OR barbiturate[tiab] OR "barbiturate derivative"[tiab] OR barbiturates[tiab] OR "barbituric acid derivative"[tiab]

#18

"4-hydroxybutyric acid"[Supplementary Concept] OR "4-hydroxybutyric acid receptor"[Supplementary Concept] OR ghba[tiab] OR "gamma hydroxy butyric acid"[tiab] OR "gamma hydroxybutyrate"[tiab] OR "gamma hydroxybutyric acid"[tiab]

#19

"Hallucinogens"[Pharmacological Action] OR "Hallucinogens"[Mesh] OR hallucinogen[tiab] OR hallucinogenic[tiab] OR "hallucinogenic agent"[tiab] OR "hallucinogenic drug"[tiab] OR hallucinogens[tiab] OR psychedelia[tiab] OR psychedelic*[tiab] OR "psychedelic agent*"[tiab] OR "psychedelic drug*"[tiab] OR psychodelic*[tiab] OR psychodysleptic[tiab] OR "psychodysleptic drug"[tiab] OR psychomimetic[tiab] OR "psychomimetic drug"[tiab] OR "psychotic drug"[tiab] OR psychotomimetic[tiab] OR "psychotomimetic agent"[tiab] OR "psychotomimetic drug*"[tiab]

#20

"Lysergic Acid Diethylamide"[Mesh] OR lsd[tiab] OR delysid[tiab] OR "l s d"[tiab] OR "lsd 25"[tiab] OR "lysergic acid diethylamide"[tiab] OR lysergide[tiab]

#21

"N-Methyl-3,4-methylenedioxymphetamine"[Mesh] OR mdma[tiab] OR ecstasy[tiab] OR methylenedioxymphetamine[tiab] OR midomafetamine[tiab]

#22

"Phencyclidine"[Mesh] OR "angel dust"[tiab] OR "ci 395"[tiab] OR ci395[tiab] OR "cl 395"[tiab] OR "gp 121"[tiab] OR phencyclidin[tiab] OR phencyclidine[tiab] OR "phencyclidine hydrochloride"[tiab] OR phenycyclidine[tiab] OR phenylcyclidine[tiab] OR sernyl[tiab] OR sernylan[tiab]

#23

"Psilocybin"[Mesh] OR comp360[tiab] OR "cy 39"[tiab] OR indocybin[tiab] OR psilocybin[tiab] OR psilocybine[tiab]

#24

"Mescaline"[Mesh] OR mescaline[tiab] OR mescaline[tiab] OR "mescaline hydrochloride"[tiab] OR mezcaline[tiab] OR peyote[tiab] OR peyotine[tiab] OR peyotl[tiab]

#25

"Ketamine"[Mesh] OR calipsol[tiab] OR calypsol[tiab] OR "ci 581"[tiab] OR ci581[tiab] OR imalgene[tiab] OR kalipsol[tiab] OR katamine[tiab] OR ketaject[tiab] OR ketalar[tiab] OR ketamine[tiab] OR "ketamine hcl"[tiab] OR "ketamine hydrochloride"[tiab] OR ketanest[tiab] OR ketased[tiab] OR ketaset[tiab] OR ketavet[tiab] OR ketolar[tiab] OR narkamon[tiab] OR "sls 002"[tiab] OR sls002[tiab] OR tekam[tiab] OR velonarcon[tiab] OR vetalar[tiab]

#26

"N,N-Dimethyltryptamine"[Mesh] OR "dimethyl tryptamine"[tiab] OR dimethyltryptamine[tiab] OR "n dimethyltryptamine"[tiab] OR "n n dimethyltryptamine"[tiab]

#27

"Central Nervous System Stimulants"[Mesh] OR analeptic*[tiab] OR "analeptic agent*"[tiab] OR "analeptic drug*"[tiab] OR analeptics[tiab] OR "psychoanaleptic agent"[tiab] OR stimulant*[tiab] OR "stimulating agent*"[tiab] OR "stimulative agent*"[tiab]

#28

"Cocaine"[Mesh] OR "Crack Cocaine"[Mesh] OR "beta cocaine"[tiab] OR cocain[tiab] OR "cocain hydrochloride"[tiab] OR cocaine[tiab] OR "cocaine hydrochloride"[tiab] OR "cocaine methiodide"[tiab] OR "crack cocaine"[tiab] OR "ecgonine methyl ester benzoate"[tiab] OR "l cocaine"[tiab] OR neurocaine[tiab]

#29

"Methamphetamine"[Mesh] OR adipex[tiab] OR ambar[tiab] OR corviten[tiab] OR deoxyephedrine[tiab] OR desamine[tiab] OR desoxyephedrine[tiab] OR "desoxyephedrine hydrochloride"[tiab] OR desoxyn[tiab] OR desyphed[tiab] OR detrex[tiab] OR "dl methamphetamine"[tiab] OR doe[tiab] OR gerovit[tiab] OR hiropon[tiab] OR isophen[tiab] OR "l methamphetamine"[tiab] OR metamphetamine[tiab] OR metamphetamine[tiab] OR methamine[tiab] OR methamphetamin[tiab] OR methamphetamine[tiab] OR "methamphetamine hcl"[tiab] OR "methamphetamine hydrochloride"[tiab] OR methedrine[tiab] OR methoxyn[tiab] OR "methyl amphetamine"[tiab] OR methylamphetamine[tiab] OR "methylamphetamine hydrochloride"[tiab] OR "n methylamphetamine"[tiab] OR norodin[tiab] OR pervitin[tiab] OR philopon[tiab]

#30

"Amphetamine"[Mesh] OR actedron[tiab] OR adipan[tiab] OR adzenys[tiab] OR "adzenys er"[tiab] OR aktedrin[tiab] OR aktedron[tiab] OR alentol[tiab] OR allodene[tiab] OR "alpha amphetamine"[tiab] OR "alpha methylphenethylamine"[tiab] OR "alpha methylphenylethylamine"[tiab] OR amfetamine[tiab] OR amphamed[tiab] OR amphamine[tiab] OR amphetaime[tiab] OR amphetamin[tiab] OR amphetamine[tiab] OR "amphetamine detection"[tiab] OR "amphetamine hydrochloride"[tiab] OR "amphetamine intoxication"[tiab] OR "amphetamine metabolism"[tiab] OR "amphetamine resin complex"[tiab] OR "amphetamine sulfate"[tiab] OR "amphetamine sulphate"[tiab] OR "amphetamine toxicity"[tiab] OR amphethamine[tiab] OR amphezamin[tiab] OR anara[tiab] OR "ar 19"[tiab] OR ar19[tiab] OR astedin[tiab] OR benzafinyl[tiab] OR benzebar[tiab] OR benzedrine[tiab] OR benzolone[tiab] OR benzpropamine[tiab] OR "beta aminopropylbenzene"[tiab] OR "beta phenyl isopropylamine"[tiab] OR "beta phenylisopropylamine"[tiab] OR betafen[tiab] OR bluzedrin[tiab] OR centramina[tiab] OR centramine[tiab] OR

"d l amphetamine"[tiab] OR "delta amphetamine"[tiab] OR diethamine[tiab] OR dipan[tiab] OR elastonin[tiab] OR elastonon[tiab] OR euphobine[tiab] OR euphodie[tiab] OR euphodyn[tiab] OR evekeo[tiab] OR "evekeo odt"[tiab] OR fabedrine[tiab] OR fenara[tiab] OR fenedrin[tiab] OR ibiozedrine[tiab] OR isoamin[tiab] OR isoamine[tiab] OR isoamyne[tiab] OR isomyn[tiab] OR "l amphetamine"[tiab] OR levamfetamine[tiab] OR "levo amphetamine"[tiab] OR levoamphetamine[tiab] OR linampheta[tiab] OR mecodrin[tiab] OR mimetina[tiab] OR monophos[tiab] OR noclon[tiab] OR norephedrane[tiab] OR norphedrane[tiab] OR novydrine[tiab] OR "nt 0201"[tiab] OR obetrol[tiab] OR oktedrin[tiab] OR oraldrina[tiab] OR ortedrine[tiab] OR percomon[tiab] OR pharmamedrine[tiab] OR pharmedrine[tiab] OR phenamin[tiab] OR phenedrine[tiab] OR phenpromin[tiab] OR "phenyl isopropylamine"[tiab] OR phenylaminopropane[tiab] OR profamina[tiab] OR profetamine[tiab] OR propisamine[tiab] OR psychedrin[tiab] OR psychedrine[tiab] OR psychoton[tiab] OR racephen[tiab] OR raphetamine[tiab] OR rhinalator[tiab] OR sedolin[tiab] OR simpamina[tiab] OR simpamine[tiab] OR simpatedrin[tiab] OR sympametin[tiab] OR sympamine[tiab] OR sympatedrine[tiab] OR theptine[tiab] OR vapedrine[tiab] OR zedrine[tiab]

#31

"Substance-Related Disorders"[Mesh] OR "Alcoholism"[Mesh] OR "Binge Drinking"[Mesh] OR "Alcohol Drinking in College"[Mesh] OR "Driving Under the Influence"[Mesh] OR "Drug Misuse"[Mesh] OR "Prescription Drug Misuse"[Mesh] OR "Inhalant Abuse"[Mesh] OR "substance usage"[tiab] OR "substance use"[tiab] OR addict[tiab] OR "addiction drug"[tiab] OR "dependence drug"[tiab] OR "drug addict"[tiab] OR "drug addiction"[tiab] OR "drug dependence"[tiab] OR "drug dependency"[tiab] OR "drug facilitation"[tiab] OR "drug habituation"[tiab] OR "physical dependence"[tiab] OR "substance addiction"[tiab] OR "substance dependence"[tiab] OR "substance dependency"[tiab] OR "substance use disorder"[tiab] OR "substance use disorders"[tiab] OR "substance-related disorder"[tiab] OR "substance related disorders"[tiab] OR toxicomania[tiab] OR toxicomanias[tiab] OR toxicomanie[tiab] OR "abuse drug"[tiab] OR "drug abuse"[tiab] OR "drug abuser"[tiab] OR "drug problem"[tiab] OR "abuse alcohol"[tiab] OR "alcohol abuse"[tiab] OR "ethanol abuse"[tiab] OR "binge drinking"[tiab] OR "heavy episodic drinking"[tiab] OR "alcohol drinking in college"[tiab] OR "college alcohol use"[tiab] OR "college drinking"[tiab] OR "college student drinking"[tiab] OR "student drinking"[tiab] OR "university student drinking"[tiab] OR "driving under the influence"[tiab] OR "driving drunken"[tiab] OR "drunk driving"[tiab] OR "drunken driver"[tiab] OR "drunken driving"[tiab] OR "excessive drinking"[tiab] OR "hazardous drinking"[tiab] OR "heavy drinking"[tiab] OR "problem drinking"[tiab] OR "problematic drinking"[tiab] OR "addiction alcohol"[tiab] OR "alcohol addiction"[tiab] OR "alcohol dependence"[tiab] OR "alcohol dependency"[tiab] OR "alcohol dependents"[tiab] OR "alcohol polyneuropathy"[tiab] OR "alcohol use disorder"[tiab] OR "alcohol-dependent individual"[tiab] OR "alcohol-induced disorders"[tiab] OR "alcohol-related disorders"[tiab] OR alcoholic[tiab] OR "alcoholic individual"[tiab] OR "alcoholic neuropathy"[tiab] OR "alcoholic polyneuritis"[tiab] OR "alcoholic polyneuropathy"[tiab] OR alcoholics[tiab] OR alcoholism[tiab] OR "chronic alcoholism"[tiab] OR "dependence alcohol"[tiab] OR dipsomania[tiab] OR dipsomaniac[tiab] OR "ethanol dependence"[tiab] OR "drug misuse"[tiab] OR "medicine misuse"[tiab] OR nmupd[tiab] OR "medication misuse"[tiab] OR "non-medical use of prescription drugs"[tiab] OR "nonmedical use of prescription drugs"[tiab] OR "prescription drug misuse"[tiab] OR "prescription medication misuse"[tiab] OR "prescription medicine misuse"[tiab] OR "glue sniffing"[tiab] OR "sniffing glue"[tiab]

#32

"Narcotics"[Pharmacological Action] OR "Narcotics"[Mesh] OR "narcotic agent*"[tiab] OR "narcotic drug*"[tiab] OR "narcotic plant"[tiab] OR narcotic*[tiab] OR stupefacient[tiab]

#33

addiction*[tiab] OR "addictive behavior*"[tiab] OR addictive[tiab] OR addict*[tiab] OR "addictive behaviour*"[tiab] OR "addictive disorder*"[tiab] OR "behavior addictive"[tiab] OR "behaviour addictive"[tiab] OR "chemical dependence"[tiab]

#34

"Illicit Drugs"[Mesh] OR "illegal drug"[tiab] OR "illegal drugs"[tiab] OR "illicit drug"[tiab] OR "illicit drugs"[tiab]

#35

"multi-drug abuse"[tiab] OR "multi-drug addiction"[tiab] OR "multidrug abuse"[tiab] OR "multiple addiction"[tiab] OR "multiple drug abuse"[tiab] OR "multiple drug addiction"[tiab] OR "poly-drug abuse"[tiab] OR "poly-drug addiction"[tiab] OR "poly-drug use"[tiab] OR "polydrug abuse"[tiab] OR "polydrug addiction"[tiab] OR "polydrug use"[tiab]

#36

"Inhalant Abuse"[Mesh] OR "inhalant abuse"[tiab] OR "inhalation abuse"[tiab] OR "inhalation drug abuse"[tiab] OR "inhalational abuse"[tiab] OR "inhalational drug abuse"[tiab]

#37

"Designer Drugs"[Mesh] OR "designer drug"[tiab] OR "designer drugs"[tiab] OR "Controlled Substances"[Mesh] OR "controlled drug"[tiab] OR "controlled drugs"[tiab] OR "controlled medicine"[tiab] OR "controlled medicines"[tiab] OR "controlled substance"[tiab] OR "controlled substances"[tiab] OR "Tobacco Products"[Mesh] OR "Tobacco Use"[Mesh] OR tobacco[tiab] OR "Nicotine"[Mesh] OR "beta pyridyl alpha n methylpyrrolidine"[tiab] OR habitrol[tiab] OR nicabate[tiab] OR nicoderm[tiab] OR "nicoderm cq"[tiab] OR nicolan[tiab] OR nicopatch[tiab] OR nicotin[tiab] OR nicotine[tiab] OR "nicotine tts"[tiab] OR nicotinell[tiab] OR "nicotinell lozenge"[tiab] OR "nicotinell tts"[tiab] OR nicotrol[tiab] OR "nicotrol inhaler"[tiab] OR "nicotrol ns"[tiab] OR niquitin[tiab] OR "niquitin cq"[tiab] OR prostep[tiab] OR "x 22"[tiab] OR x22[tiab]

#38

"Designer Drugs"[Mesh] OR "designer drug"[tiab] OR "designer drugs"[tiab] OR "Controlled Substances"[Mesh] OR "controlled drug"[tiab] OR "controlled drugs"[tiab] OR "controlled medicine"[tiab] OR "controlled medicines"[tiab] OR "controlled substance"[tiab] OR "controlled substances"[tiab] OR tobacco[tiab] OR "Nicotine"[Mesh] OR "beta pyridyl alpha n methylpyrrolidine"[tiab] OR habitrol[tiab] OR nicabate[tiab] OR nicoderm[tiab] OR "nicoderm cq"[tiab] OR nicolan[tiab] OR nicopatch[tiab] OR nicotin[tiab] OR nicotine[tiab] OR "nicotine tts"[tiab] OR nicotinell[tiab] OR "nicotinell lozenge"[tiab] OR "nicotinell tts"[tiab] OR nicotrol[tiab] OR "nicotrol inhaler"[tiab] OR "nicotrol ns"[tiab] OR niquitin[tiab] OR "niquitin cq"[tiab] OR prostep[tiab] OR "x 22"[tiab] OR x22[tiab] OR "Smoking"[Mesh] OR "behavior smoking"[tiab] OR "behaviour smoking"[tiab] OR "reverse smoking"[tiab] OR smoker[tiab] OR smokers[tiab] OR smoking[tiab] OR "smoking behavior"[tiab] OR "smoking behaviour"[tiab] OR "tobacco smoking"[tiab] OR "Cigarette Smoking"[Mesh] OR "Vaping"[Mesh] OR "Electronic Nicotine Delivery Systems"[Mesh] OR "E-Cigarette Vapor"[Mesh] OR cigarette*[tiab] OR "filter cigarette"[tiab] OR "e cigarette"[tiab] OR "e cigarettes"[tiab] OR "electronic cigarette"[tiab] OR "electronic cigarettes"[tiab] OR "electronic nicotine delivery system"[tiab] OR "electronic nicotine delivery systems"[tiab] OR "e-cigarette smoking"[tiab] OR "electronic cigarette smoking"[tiab] OR vaping[tiab] OR vape*[tiab] OR cigar*[tiab] OR "Tobacco, Waterpipe"[Mesh] OR "Water Pipe Smoking"[Mesh] OR "Smoking Water Pipes"[Mesh] OR arghile[tiab] OR goza[tiab] OR hookah[tiab] OR narghile[tiab] OR shisha[tiab] OR "smoking water pipe"[tiab] OR "smoking water pipes"[tiab]

#39

"Nitrous Oxide"[Mesh] OR "dinitrogen monoxide"[tiab] OR "dinitrogen oxide"[tiab] OR "factitious air"[tiab] OR "hyponitrous acid anhydride"[tiab] OR lachgas[tiab] OR "laughing gas"[tiab] OR "nitrogen hypoxide"[tiab] OR "nitrogen protoxide"[tiab] OR "nitrous oxide"[tiab] OR whippet*[tiab] OR nangs[tiab] OR "buzz bomb*[tiab] OR "hippy crack"[tiab]

#40

#1 OR #2 OR #3 OR #4 OR #5 OR #6 OR #7 OR #8 OR #9 OR #10 OR #11 OR #12 OR #13 OR #14 OR #15 OR #16 OR #17 OR #18 OR #19 OR #20 OR #21 OR #22 OR #23 OR #24 OR #25 OR #26 OR #27 OR #28 OR #29 OR #30 OR #31 OR #32 OR #33 OR #34 OR #35 OR #36 OR #37 OR #38 OR #39

#41

"text analytic*" [tiab] OR "text information extraction" [tiab] OR "named entity extraction" [tiab] OR "named entity recognition" [tiab] OR "co-reference resolution" [tiab] OR "relation extraction" [tiab] OR "Sentiment Analysis" [Mesh] OR "emotion ai" [tiab] OR "opinion mining" [tiab] OR "sentiment analysis" [tiab] OR "topic modeling" [tiab] OR "word embedding" [tiab]

#42

"language model*" [tiab] OR "large language model*" [tiab] OR "generative pre-trained transformer" [tiab] OR "generative pre-training transformer" [tiab] OR "generative pretrained transformer" [tiab] OR "transformer model*" [tiab] OR "bidirectional encoder representations from transformer*" [tiab] OR "few shot learning" [tiab] OR "zero shot learning" [tiab] OR "prompt engineering" [tiab] OR "text classification*" [tiab] OR "Word Processing" [Mesh] OR "text processing" [tiab] OR "word processing" [tiab] OR "syntactic parsing" [tiab] OR "semantic analysis" [tiab] OR "semantic analytic*" [tiab] OR "discourse analysis" [tiab] OR "text summarization" [tiab]

#43

"Neural Networks, Computer" [Mesh] OR "mlp multilayer perceptron" [tiab] OR "mlp neural network" [tiab] OR "multi-layer perceptron" [tiab] OR "multilayer perceptron" [tiab] OR "multilayer perceptron network" [tiab] OR "multilayer perceptron neural network" [tiab] OR "multiple layer perceptron" [tiab] OR "cnn convolutional neural network" [tiab] OR "cnns convolutional neural networks" [tiab] OR convnet [tiab] OR "convoluted neural network" [tiab] OR "convolution neural network" [tiab] OR "convolutional anns" [tiab] OR "convolutional nn" [tiab] OR "convolutional artificial neural network" [tiab] OR "convolutional deep neural network" [tiab] OR "convolutional neural network" [tiab] OR "deep convolutional neural network" [tiab] OR "recursive neural network" [tiab] OR "rnn recurrent neural network" [tiab] OR "rnns recurrent neural networks" [tiab] OR "recurrent ann" [tiab] OR "recurrent nn" [tiab] OR "recurrent nns" [tiab] OR "recurrent artificial neural network" [tiab] OR "recurrent neural network" [tiab] OR "lstm model" [tiab] OR "lstm network" [tiab] OR "lstm neural network" [tiab] OR "lstm recurrent neural network" [tiab] OR "lstm-rnn" [tiab] OR "lstm-rnns" [tiab] OR "rnn-lstm" [tiab] OR "long short term memory lstm network" [tiab] OR "long short term memory lstm neural network" [tiab] OR "long short term memory neural network" [tiab] OR "long short term memory network" [tiab] OR "long short-term memory recurrent neural network" [tiab] OR "sequence to sequence model*" [tiab] OR "shallow neural network*" [tiab] OR "ann artificial neural network" [tiab] OR "ann analysis" [tiab] OR "ann approach" [tiab] OR "ann method" [tiab] OR "ann methodology" [tiab] OR "ann methods" [tiab] OR "ann model" [tiab] OR "ann modeling" [tiab] OR "ann modelling" [tiab] OR "ann models" [tiab] OR "ann output" [tiab] OR "ann technique" [tiab] OR "ann techniques" [tiab] OR "ann training" [tiab] OR "anns artificial neural networks" [tiab] OR "artificial nn" [tiab] OR "artificial nns" [tiab] OR "artificial neural network" [tiab] OR "artificial neural networks" [tiab] OR "computational neural network" [tiab] OR "computer neural network" [tiab] OR "computer neural networks" [tiab] OR "connectionist model" [tiab] OR "connectionist network" [tiab] OR "connectionist neural network" [tiab] OR "connectionist system" [tiab] OR "mathematical neural network" [tiab] OR "neural network computer" [tiab] OR "neural network algorithm" [tiab] OR "neural network model" [tiab] OR "neural networks computer" [tiab] OR "clinical note*" [tiab] OR "free text*" [tiab]

#44

"Natural Language Processing" [Mesh] OR "natural language processing" [tiab] OR "text mining" [tiab] OR "text mine*" [tiab]

#45

#41 OR #42 OR #43 OR #44

#46

"Electronic Health Records" [Mesh] OR "ehr electronic health record" [tiab] OR "electronic health record" [tiab] OR "electronic health records" [tiab] OR "electronic healthcare database" [tiab] OR "electronic medical record" [tiab] OR "Telemedicine" [Mesh] OR "e-health" [tiab] OR ehealth [tiab] OR "tele-health" [tiab] OR telehealth [tiab] OR "tele medicine" [tiab] OR telemedicine [tiab] OR "virtual medicine" [tiab] OR "m health" [tiab] OR "e visit*" [tiab]

#47

	#40 AND #45 AND #46
	#48
	#40 AND #45 AND #46
	Filters: English
COCHRANE LIBRARY	#1 "Analgesics, Opioid":MH OR algopan:ti,ab OR biopon:ti,ab OR laudanum:ti,ab OR nepenthe:ti,ab OR omnopon:ti,ab OR opial:ti,ab OR opiate*:ti,ab OR "opiate alkaloid":ti,ab OR "opiate alkaloids":ti,ab OR opioid*:ti,ab OR opium:ti,ab OR "opium alkaloid":ti,ab OR "opium alkaloids":ti,ab OR "opium derivative":ti,ab OR "opium poppy":ti,ab OR "opium tincture":ti,ab OR opon:ti,ab OR pantopon:ti,ab OR papaveretum:ti,ab OR pavon:ti,ab OR tetrapon:ti,ab
	#2 "Heroin":MH OR acetomorphine:ti,ab OR "diacetyl morphine":ti,ab OR diacetylmorphine:ti,ab OR "diacetylmorphine hydrochloride":ti,ab OR diamorphine:ti,ab OR "diamorphine hydrochloride":ti,ab OR diaphorin:ti,ab OR heroin:ti,ab OR "heroin hydrochloride":ti,ab OR heroine:ti,ab OR morphacetin:ti,ab
	#3 "Oxycodone":MH OR alivio:ti,ab OR bionone:ti,ab OR "col 003":ti,ab OR col003:ti,ab OR dihydrohydroxycodone:ti,ab OR dihydrone:ti,ab OR endone:ti,ab OR eubine:ti,ab OR eucodal:ti,ab OR eucodolum:ti,ab OR eukodal:ti,ab OR nargenol:ti,ab OR "nsc 19043":ti,ab OR opton:ti,ab OR ossicodone:ti,ab OR oxanest:ti,ab OR oxaydo:ti,ab OR oxecta:ti,ab OR oxiconona:ti,ab OR oxicone:ti,ab OR "oxy ir":ti,ab OR oxycodon:ti,ab OR oxycodone:ti,ab OR "oxycodone hcl":ti,ab OR "oxycodone hydrochloride":ti,ab OR oxycone:ti,ab OR oxycontin:ti,ab OR "oxycontin neo":ti,ab OR oxydol:ti,ab OR oxyfast:ti,ab OR oxygesic:ti,ab OR oxyir:ti,ab OR oxylan:ti,ab OR oxyneo:ti,ab OR oxynorm:ti,ab OR oxypro:ti,ab OR pavinal:ti,ab OR pronarcin:ti,ab OR "pti 821":ti,ab OR pti821:ti,ab OR remoxy:ti,ab OR roxicodone:ti,ab OR roxybond:ti,ab OR xtampza:ti,ab OR "xtampza er":ti,ab
	#4 "Hydrocodone":MH OR bekadid:ti,ab OR dico:ti,ab OR dicodid:ti,ab OR dihydrocodeinone:ti,ab OR hydrocodone:ti,ab OR hydrocodonum:ti,ab
	#5 "Fentanyl":MH OR "ap 48":ti,ab OR ap48:ti,ab OR "az 003":ti,ab OR az003:ti,ab OR duragesic:ti,ab OR "duragesic-100":ti,ab OR "duragesic-12":ti,ab OR "duragesic-25":ti,ab OR "duragesic-50":ti,ab OR "duragesic-75":ti,ab OR durogesic:ti,ab OR durotep:ti,ab OR fentamyl:ti,ab OR fentanil:ti,ab OR fentanyl:ti,ab OR "fentanyl buccal soluble film":ti,ab OR "fentanyl hydrochloride":ti,ab OR "fentanyl iontophoretic":ti,ab OR "fentanyl-100":ti,ab OR "fentanyl-12":ti,ab OR "fentanyl-25":ti,ab OR "fentanyl-37":ti,ab OR "fentanyl-50":ti,ab OR "fentanyl-75":ti,ab OR jns020qd:ti,ab OR leptanal:ti,ab OR matrifen:ti,ab OR pecfent:ti,ab OR phentanyl:ti,ab OR "r 4263":ti,ab OR r4263:ti,ab OR recuvyra:ti,ab OR subsys:ti,ab OR tanyl:ti,ab
	#6 "Morphine":MH OR anpec:ti,ab OR duromorph:ti,ab OR epimorph:ti,ab OR miro:ti,ab OR morfin:ti,ab OR morfine:ti,ab OR morphia:ti,ab OR morphin:ti,ab OR morphine:ti,ab OR "morphine alkaloid":ti,ab OR "morphine chlorhydrate":ti,ab OR "morphine chloride":ti,ab OR "morphine hydrochloride":ti,ab OR "morphine suspension":ti,ab OR morphinium:ti,ab OR morphium:ti,ab OR opso:ti,ab OR skenan:ti,ab OR "trans morphine":ti,ab
	#7 "Codeine":MH OR codein:ti,ab OR codeine:ti,ab OR codipertussin:ti,ab OR codyl:ti,ab OR "methyl morphine":ti,ab OR methyilmorphine:ti,ab OR "morphine 3 methyl ether":ti,ab OR "morphine monomethyl ether":ti,ab OR "trans codeine":ti,ab
	#8 "Methadone":MH OR adanon:ti,ab OR algolysin:ti,ab OR algovetin:ti,ab OR amidon:ti,ab OR amidone:ti,ab OR "an 148":ti,ab OR an148:ti,ab OR anadon:ti,ab OR butalgin:ti,ab OR deamin:ti,ab OR depridol:ti,ab OR diaminon:ti,ab OR dolamid:ti,ab OR dolmed:ti,ab OR dolophin:ti,ab OR dolophine:ti,ab OR dorex:ti,ab OR eptadone:ti,ab OR fenadon:ti,ab OR heptadon:ti,ab OR heptadone:ti,ab OR heptanon:ti,ab OR ketalgin:ti,ab OR "l-polamidon":ti,ab OR mecodin:ti,ab OR metadol:ti,ab OR metadon:ti,ab OR methaddict:ti,ab OR methadon:ti,ab OR methadone:ti,ab OR

"methadone base":ti,ab OR "methadone hydrochloride":ti,ab OR methadose:ti,ab OR miadone:ti,ab OR phenadon:ti,ab OR physeptone:ti,ab OR polamidon:ti,ab OR polamivet:ti,ab OR "sedo-rapide":ti,ab OR symoron:ti,ab OR win:ti,ab

#9 "Buprenorphine":MH OR addnok:ti,ab OR astec:ti,ab OR belbuca:ti,ab OR brixadi:ti,ab OR buprenex:ti,ab OR buprenorfin:ti,ab OR buprenorfina:ti,ab OR buprenorfine:ti,ab OR buprenorphin:ti,ab OR buprenorphine:ti,ab OR "buprenorphine hydrochloride":ti,ab OR butec:ti,ab OR butrans:ti,ab OR buvidal:ti,ab OR cam2038:ti,ab OR lepetan:ti,ab OR "lyn 013":ti,ab OR lyn013:ti,ab OR norphin:ti,ab OR norspan:ti,ab OR probuphenine:ti,ab OR probuphine:ti,ab OR "rbp 6000":ti,ab OR rbp6000:ti,ab OR sixmo:ti,ab OR sublocade:ti,ab OR subutex:ti,ab OR temgesic:ti,ab OR transtec:ti,ab

#10 "Tramadol":MH OR ad2112:ti,ab OR adamon:ti,ab OR adolonta:ti,ab OR amanda:ti,ab OR analab:ti,ab OR andalpha:ti,ab OR bio301:ti,ab OR calmol:ti,ab OR "cg 315":ti,ab OR "cg 315e":ti,ab OR cg315:ti,ab OR contramal:ti,ab OR conzip:ti,ab OR dolzam:ti,ab OR "e 382":ti,ab OR e381:ti,ab OR e382:ti,ab OR marol:ti,ab OR monocriox:ti,ab OR noax:ti,ab OR nobligan:ti,ab OR "ns 24":ti,ab OR ns24:ti,ab OR prontalgin:ti,ab OR qdolo:ti,ab OR ralivia:ti,ab OR ryzolt:ti,ab OR "t-long":ti,ab OR tioner:ti,ab OR tiparol:ti,ab OR topalgic:ti,ab OR "topalgic lp":ti,ab OR toram:ti,ab OR tradolan:ti,ab OR tradonal:ti,ab OR tralgit:ti,ab OR tramadol:ti,ab OR "tramadol hcl":ti,ab OR "tramadol hydrochloride":ti,ab OR "tramadol lp":ti,ab OR "tramadol retard":ti,ab OR "tramadol sr":ti,ab OR tramadolis:ti,ab OR tramadolo:ti,ab OR tramadolor:ti,ab OR tramal:ti,ab OR tramazac:ti,ab OR tramol:ti,ab OR tramundin:ti,ab OR tridol:ti,ab OR tridural:ti,ab OR trodon:ti,ab OR ultram:ti,ab OR "ultram er":ti,ab OR zamadol:ti,ab OR zertane:ti,ab OR zydol:ti,ab OR "zydol sr":ti,ab OR zytram:ti,ab

#11 "Hydromorphone":MH OR dihydromorphinone:ti,ab OR dihydromorphone:ti,ab OR dilaudid:ti,ab OR dimorphone:ti,ab OR exalgo:ti,ab OR "hydromorph contin":ti,ab OR hydromorphon:ti,ab OR hydromorphone:ti,ab OR "hydromorphone hydrochloride":ti,ab OR jurnista:ti,ab OR novolaudon:ti,ab OR palladon:ti,ab OR palladone:ti,ab

#12 "Oxymorphone":MH OR hydroxydihydromorphinone:ti,ab OR numorphan:ti,ab OR opana:ti,ab OR "opana er":ti,ab OR oxymorphone:ti,ab OR "oxymorphone hydrochloride":ti,ab

#13 "Cannabinoids":MH OR "Cannabis":MH OR cannabinoid:ti,ab OR cannabinoids:ti,ab OR "cannabis sativa extract":ti,ab OR "cannabis sativa resin":ti,ab OR bhang:ti,ab OR cannabis:ti,ab OR "cannabis constituent":ti,ab OR "cannabis extract":ti,ab OR "cannabis leaf":ti,ab OR cannador:ti,ab OR charas:ti,ab OR ganja:ti,ab OR hashish:ti,ab OR "hashish oil":ti,ab OR "hemp extract":ti,ab OR marihuana:ti,ab OR marijuana:ti,ab OR "Medical Marijuana":MH OR "medical cannabis":ti,ab OR "medical marihuana":ti,ab OR "medical marijuana":ti,ab OR "medicinal cannabis":ti,ab OR "medicinal marijuana":ti,ab OR "marijuana treatment":ti,ab OR "Dronabinol":MH OR "1 trans delta 9 tetrahydrocannabinol":ti,ab OR "delta 1 tetrahydrocannabinol":ti,ab OR "delta 1 trans tetrahydrocannabinol":ti,ab OR "delta 9 tetrahydrocannabinol":ti,ab OR "delta 9 trans tetrahydrocannabinol":ti,ab OR "delta1 tetrahydrocannabinol":ti,ab OR "delta1 thc":ti,ab OR "delta1 trans tetrahydrocannabinol":ti,ab OR "delta9 tetrahydro cannabinol":ti,ab OR "delta9 tetrahydrocannabinol":ti,ab OR "delta9 trans tetrahydrocannabinol":ti,ab OR dronabinol:ti,ab OR "1 delta 9 trans tetrahydrocannabinol":ti,ab OR marinol:ti,ab OR "qcd 84924":ti,ab OR syndros:ti,ab OR "tetrahydrocannabinol delta9":ti,ab OR "trans delta 9 tetrahydrocannabinol":ti,ab OR thc:ti,ab OR "delta 3 tetrahydrocannabinol":ti,ab OR "delta tetrahydrocannabinol":ti,ab OR "delta3 tetrahydrocannabinol":ti,ab OR "sp 104":ti,ab OR "tetrahydro cannabinol":ti,ab OR tetrahydrocannabinol:ti,ab OR tetrahydrocannabinol:ti,ab OR tetrahydrocannabinol:ti,ab OR "trans tetrahydrocannabinol":ti,ab OR scb:ti,ab

#14 "Ethanol":MH OR alcohol:ti,ab OR ethanol:ti,ab OR ethylalcohol:ti,ab

#15 "Alcoholic Beverages":MH OR "Absinthe":MH OR "Beer":MH OR "Wine":MH OR "alcoholic beverage":ti,ab OR "alcoholic beverages":ti,ab OR "alcoholic drink":ti,ab OR "liquor alcohol":ti,ab OR absinthe:ti,ab OR beer:ti,ab OR brandy:ti,ab OR gin:ti,ab OR makgeolli:ti,ab OR makkoli:ti,ab OR makoli:ti,ab OR "honey wine":ti,ab OR pulque:ti,ab OR rum:ti,ab OR "rice wine":ti,ab OR sake:ti,ab OR

vodka:ti,ab OR bourbon:ti,ab OR "bourbon whiskey":ti,ab OR "scotch whiskey":ti,ab OR whiskey:ti,ab OR whisky:ti,ab OR wine:ti,ab OR "apple cider":ti,ab OR "apple wine":ti,ab OR cider:ti,ab

#16 "Benzodiazepines":MH OR benzodiazepine:ti,ab OR benzodiazepines:ti,ab

#17 "Phenobarbital":MH OR barbiturate:ti,ab OR "barbiturate derivative":ti,ab OR barbiturates:ti,ab OR "barbituric acid derivative":ti,ab

#18 ghba:ti,ab OR "gamma hydroxy butyric acid":ti,ab OR "gamma hydroxybutyrate":ti,ab OR "gamma hydroxybutyric acid":ti,ab

#19 "Hallucinogens":MH OR hallucinogen:ti,ab OR hallucinogenic:ti,ab OR "hallucinogenic agent":ti,ab OR "hallucinogenic drug":ti,ab OR hallucinogens:ti,ab OR psychedelia:ti,ab OR psychedelic*:ti,ab OR "psychedelic agent*":ti,ab OR "psychedelic drug*":ti,ab OR psychedelic*:ti,ab OR psychodysleptic:ti,ab OR "psychodysleptic drug":ti,ab OR psychomimetic:ti,ab OR "psychomimetic drug":ti,ab OR "psychotic drug":ti,ab OR psychotomimetic:ti,ab OR "psychotomimetic agent":ti,ab OR "psychotomimetic drug*":ti,ab

#20 "Lysergic Acid Diethylamide":MH OR lsd:ti,ab OR delysid:ti,ab OR "l s d":ti,ab OR "lsd 25":ti,ab OR "lysergic acid diethylamide":ti,ab OR lysergide:ti,ab

#21 mdma:ti,ab OR ecstasy:ti,ab OR methylenedioxyamphetamine:ti,ab OR midomafetamine:ti,ab

#22 "Phencyclidine":MH OR "angel dust":ti,ab OR "ci 395":ti,ab OR ci395:ti,ab OR "cl 395":ti,ab OR "gp 121":ti,ab OR phencyclidin:ti,ab OR phencyclidine:ti,ab OR "phencyclidine hydrochloride":ti,ab OR phenycyclidine:ti,ab OR phenylcyclidine:ti,ab OR sernyl:ti,ab OR sernylan:ti,ab

#23 "Psilocybin":MH OR comp360:ti,ab OR "cy 39":ti,ab OR indocybin:ti,ab OR psilocybin:ti,ab OR psilocybine:ti,ab

#24 "Mescaline":MH OR mescaline:ti,ab OR mescaline:ti,ab OR "mescaline hydrochloride":ti,ab OR mezcaline:ti,ab OR peyote:ti,ab OR peyotine:ti,ab OR peyotl:ti,ab

#25 "Ketamine":MH OR calipsol:ti,ab OR calypsol:ti,ab OR "ci 581":ti,ab OR ci581:ti,ab OR imalgene:ti,ab OR kalipsol:ti,ab OR katamine:ti,ab OR ketaject:ti,ab OR ketalar:ti,ab OR ketamine:ti,ab OR "ketamine hcl":ti,ab OR "ketamine hydrochloride":ti,ab OR ketanest:ti,ab OR ketased:ti,ab OR ketaset:ti,ab OR ketavet:ti,ab OR ketolar:ti,ab OR narkamon:ti,ab OR "sls 002":ti,ab OR sls002:ti,ab OR tekam:ti,ab OR velonarcon:ti,ab OR vetalar:ti,ab

#26 "dimethyl tryptamine":ti,ab OR dimethyltryptamine:ti,ab OR "n dimethyltryptamine":ti,ab OR "n n dimethyltryptamine":ti,ab

#27 "Central Nervous System Stimulants":MH OR analeptic*:ti,ab OR "analeptic agent*":ti,ab OR "analeptic drug*":ti,ab OR analeptics:ti,ab OR "psychoanaleptic agent":ti,ab OR stimulant*:ti,ab OR "stimulating agent*":ti,ab OR "stimulative agent*":ti,ab

#28 "Cocaine":MH OR "Crack Cocaine":MH OR "beta cocaine":ti,ab OR cocain:ti,ab OR "cocain hydrochloride":ti,ab OR cocaine:ti,ab OR "cocaine hydrochloride":ti,ab OR "cocaine methiodide":ti,ab OR "crack cocaine":ti,ab OR "ecgonine methyl ester benzoate":ti,ab OR "l cocaine":ti,ab OR neurocaine:ti,ab

#29 "Methamphetamine":MH OR adipex:ti,ab OR ambar:ti,ab OR corvitin:ti,ab OR deoxyephedrine:ti,ab OR desamine:ti,ab OR desoxyephedrine:ti,ab OR "desoxyephedrine hydrochloride":ti,ab OR desoxyn:ti,ab OR desyphed:ti,ab OR detrex:ti,ab OR "dl methamphetamine":ti,ab OR doe:ti,ab OR gerovit:ti,ab OR hiropon:ti,ab OR isophen:ti,ab OR "l methamphetamine":ti,ab OR metamfetamine:ti,ab

OR metamphetamine:ti,ab OR methamine:ti,ab OR methamphetamin:ti,ab OR methamphetamine:ti,ab OR "methamphetamine hcl":ti,ab OR "methamphetamine hydrochloride":ti,ab OR methedrine:ti,ab OR methoxyn:ti,ab OR "methyl amphetamine":ti,ab OR methylamphetamine:ti,ab OR "methylamphetamine hydrochloride":ti,ab OR "n methylamphetamine":ti,ab OR norodin:ti,ab OR pervitin:ti,ab OR philopon:ti,ab

#30 "Amphetamine":MH OR actedron:ti,ab OR adipan:ti,ab OR adzenys:ti,ab OR "adzenys er":ti,ab OR aktedrin:ti,ab OR aktedron:ti,ab OR alentol:ti,ab OR allodene:ti,ab OR "alpha amphetamine":ti,ab OR "alpha methylphenethylamine":ti,ab OR "alpha methylphenylethylamine":ti,ab OR amfetamine:ti,ab OR amphamed:ti,ab OR amphamine:ti,ab OR amphetaime:ti,ab OR amphetamin:ti,ab OR amphetamine:ti,ab OR "amphetamine detection":ti,ab OR "amphetamine hydrochloride":ti,ab OR "amphetamine intoxication":ti,ab OR "amphetamine metabolism":ti,ab OR "amphetamine resin complex":ti,ab OR "amphetamine sulfate":ti,ab OR "amphetamine sulphate":ti,ab OR "amphetamine toxicity":ti,ab OR amphetamine:ti,ab OR amphezamin:ti,ab OR anara:ti,ab OR "ar 19":ti,ab OR ar19:ti,ab OR astedin:ti,ab OR benzafinyl:ti,ab OR benzebar:ti,ab OR benzedrine:ti,ab OR benzolone:ti,ab OR benzpropamine:ti,ab OR "beta aminopropylbenzene":ti,ab OR "beta phenyl isopropylamine":ti,ab OR "beta phenylisopropylamine":ti,ab OR betafen:ti,ab OR bluzedrin:ti,ab OR centramina:ti,ab OR centramine:ti,ab OR "d l amphetamine":ti,ab OR "delta amphetamine":ti,ab OR diethamine:ti,ab OR dipan:ti,ab OR elastonin:ti,ab OR elastonon:ti,ab OR euphobine:ti,ab OR euphodyne:ti,ab OR euphodyn:ti,ab OR evekeo:ti,ab OR "evekeo odt":ti,ab OR fabedrine:ti,ab OR fenara:ti,ab OR fenedrin:ti,ab OR ibiozedrine:ti,ab OR isoamin:ti,ab OR isoamine:ti,ab OR isoamyne:ti,ab OR isomyn:ti,ab OR "l amphetamine":ti,ab OR levamfetamine:ti,ab OR "levo amphetamine":ti,ab OR levoamphetamine:ti,ab OR linampheta:ti,ab OR mecodrin:ti,ab OR mimetina:ti,ab OR monophos:ti,ab OR noclon:ti,ab OR norephedrane:ti,ab OR norphedrane:ti,ab OR novydrine:ti,ab OR "nt 0201":ti,ab OR obetrol:ti,ab OR oktedrin:ti,ab OR oraldrina:ti,ab OR ortedrine:ti,ab OR percomon:ti,ab OR pharmamedrine:ti,ab OR pharmedrine:ti,ab OR phenamin:ti,ab OR phenedrine:ti,ab OR phenpromin:ti,ab OR "phenyl isopropylamine":ti,ab OR phenylaminopropane:ti,ab OR profamina:ti,ab OR profetamine:ti,ab OR propisamine:ti,ab OR psychedrin:ti,ab OR psychedrine:ti,ab OR psychoton:ti,ab OR racephen:ti,ab OR raphetamine:ti,ab OR rhinalator:ti,ab OR sedolin:ti,ab OR simpamina:ti,ab OR simpamine:ti,ab OR simpatedrin:ti,ab OR sympametin:ti,ab OR sympamine:ti,ab OR sympatedrine:ti,ab OR theptine:ti,ab OR vapedrine:ti,ab OR zedrine:ti,ab

#31 "Substance-Related Disorders":MH OR "Alcoholism":MH OR "Binge Drinking":MH OR "Alcohol Drinking in College":MH OR "Driving Under the Influence":MH OR "Drug Misuse":MH OR "Prescription Drug Misuse":MH OR "Inhalant Abuse":MH OR "substance usage":ti,ab OR "substance use":ti,ab OR addict:ti,ab OR "addiction drug":ti,ab OR "dependence drug":ti,ab OR "drug addict":ti,ab OR "drug addiction":ti,ab OR "drug dependence":ti,ab OR "drug dependency":ti,ab OR "drug facilitation":ti,ab OR "drug habituation":ti,ab OR "physical dependence":ti,ab OR "substance addiction":ti,ab OR "substance dependence":ti,ab OR "substance dependency":ti,ab OR "substance use disorder":ti,ab OR "substance use disorders":ti,ab OR "substance-related disorder":ti,ab OR "substance related disorders":ti,ab OR toxicomania:ti,ab OR toxicomanias:ti,ab OR toxicomanic:ti,ab OR "abuse drug":ti,ab OR "drug abuse":ti,ab OR "drug abuser":ti,ab OR "drug problem":ti,ab OR "abuse alcohol":ti,ab OR "alcohol abuse":ti,ab OR "ethanol abuse":ti,ab OR "binge drinking":ti,ab OR "heavy episodic drinking":ti,ab OR "alcohol drinking in college":ti,ab OR "college alcohol use":ti,ab OR "college drinking":ti,ab OR "college student drinking":ti,ab OR "student drinking":ti,ab OR "university student drinking":ti,ab OR "driving under the influence":ti,ab OR "driving drunken":ti,ab OR "drunk driving":ti,ab OR "drunken driver":ti,ab OR "drunken driving":ti,ab OR "excessive drinking":ti,ab OR "hazardous drinking":ti,ab OR "heavy drinking":ti,ab OR "problem drinking":ti,ab OR "problematic drinking":ti,ab OR "addiction alcohol":ti,ab OR "alcohol addiction":ti,ab OR "alcohol dependence":ti,ab OR "alcohol dependency":ti,ab OR "alcohol dependents":ti,ab OR "alcohol polyneuropathy":ti,ab OR "alcohol use disorder":ti,ab OR "alcohol-dependent individual":ti,ab OR "alcohol-induced disorders":ti,ab OR "alcohol-related disorders":ti,ab OR alcoholic:ti,ab OR "alcoholic individual":ti,ab OR "alcoholic neuropathy":ti,ab OR "alcoholic polyneuritis":ti,ab OR "alcoholic polyneuropathy":ti,ab OR alcoholics:ti,ab OR alcoholism:ti,ab OR "chronic alcoholism":ti,ab OR "dependence alcohol":ti,ab OR dipsomania:ti,ab OR dipsomaniac:ti,ab OR "ethanol dependence":ti,ab OR "drug misuse":ti,ab OR "medicine misuse":ti,ab OR nmupd:ti,ab OR "medication misuse":ti,ab OR "non-medical use of prescription drugs":ti,ab OR "nonmedical use of prescription drugs":ti,ab OR "prescription drug misuse":ti,ab OR "prescription medication misuse":ti,ab OR "prescription medicine misuse":ti,ab OR "glue sniffing":ti,ab OR "sniffing glue":ti,ab

#32 "Narcotics":MH OR "narcotic agent*":ti,ab OR "narcotic drug*":ti,ab OR "narcotic plant":ti,ab OR narcotic*:ti,ab OR stupefacient:ti,ab

#33 addiction*:ti,ab OR "addictive behavior*":ti,ab OR addictive:ti,ab OR addict*:ti,ab OR "addictive behaviour*":ti,ab OR "addictive disorder*":ti,ab OR "behavior addictive":ti,ab OR "behaviour addictive":ti,ab OR "chemical dependence":ti,ab

#34 "Illicit Drugs":MH OR "illegal drug":ti,ab OR "illegal drugs":ti,ab OR "illicit drug":ti,ab OR "illicit drugs":ti,ab

#35 "multi-drug abuse":ti,ab OR "multi-drug addiction":ti,ab OR "multidrug abuse":ti,ab OR "multiple addiction":ti,ab OR "multiple drug abuse":ti,ab OR "multiple drug addiction":ti,ab OR "poly-drug abuse":ti,ab OR "poly-drug addiction":ti,ab OR "poly-drug use":ti,ab OR "polydrug abuse":ti,ab OR "polydrug addiction":ti,ab OR "polydrug use":ti,ab

#36 "Inhalant Abuse":MH OR "inhalant abuse":ti,ab OR "inhalation abuse":ti,ab OR "inhalation drug abuse":ti,ab OR "inhalational abuse":ti,ab OR "inhalational drug abuse":ti,ab

#37 "Designer Drugs":MH OR "designer drug":ti,ab OR "designer drugs":ti,ab OR "Controlled Substances":MH OR "controlled drug":ti,ab OR "controlled drugs":ti,ab OR "controlled medicine":ti,ab OR "controlled medicines":ti,ab OR "controlled substance":ti,ab OR "controlled substances":ti,ab OR "Tobacco Products":MH OR "Tobacco Use":MH OR tobacco:ti,ab OR "Nicotine":MH OR "beta pyridyl alpha n methylpyrrolidine":ti,ab OR habitrol:ti,ab OR nicabate:ti,ab OR nicoderm:ti,ab OR "nicoderm cq":ti,ab OR nicolan:ti,ab OR nicopatch:ti,ab OR nicotin:ti,ab OR nicotine:ti,ab OR "nicotine tts":ti,ab OR nicotinell:ti,ab OR "nicotinell lozenge":ti,ab OR "nicotinell tts":ti,ab OR nicotrol:ti,ab OR "nicotrol inhaler":ti,ab OR "nicotrol ns":ti,ab OR niquitin:ti,ab OR "niquitin cq":ti,ab OR prostep:ti,ab OR "x 22":ti,ab OR x22:ti,ab

#38 "Designer Drugs":MH OR "designer drug":ti,ab OR "designer drugs":ti,ab OR "Controlled Substances":MH OR "controlled drug":ti,ab OR "controlled drugs":ti,ab OR "controlled medicine":ti,ab OR "controlled medicines":ti,ab OR "controlled substance":ti,ab OR "controlled substances":ti,ab OR tobacco:ti,ab OR "Nicotine":MH OR "beta pyridyl alpha n methylpyrrolidine":ti,ab OR habitrol:ti,ab OR nicabate:ti,ab OR nicoderm:ti,ab OR "nicoderm cq":ti,ab OR nicolan:ti,ab OR nicopatch:ti,ab OR nicotin:ti,ab OR nicotine:ti,ab OR "nicotine tts":ti,ab OR nicotinell:ti,ab OR "nicotinell lozenge":ti,ab OR "nicotinell tts":ti,ab OR nicotrol:ti,ab OR "nicotrol inhaler":ti,ab OR "nicotrol ns":ti,ab OR niquitin:ti,ab OR "niquitin cq":ti,ab OR prostep:ti,ab OR "x 22":ti,ab OR x22:ti,ab OR "Smoking":MH OR "behavior smoking":ti,ab OR "behaviour smoking":ti,ab OR "reverse smoking":ti,ab OR smoker:ti,ab OR smokers:ti,ab OR smoking:ti,ab OR "smoking behavior":ti,ab OR "smoking behaviour":ti,ab OR "tobacco smoking":ti,ab OR "Cigarette Smoking":MH OR "Vaping":MH OR "Electronic Nicotine Delivery Systems":MH OR cigarette*:ti,ab OR "filter cigarette":ti,ab OR "e cigarette":ti,ab OR "e cigarettes":ti,ab OR "electronic cigarette":ti,ab OR "electronic cigarettes":ti,ab OR "electronic nicotine delivery system":ti,ab OR "electronic nicotine delivery systems":ti,ab OR "e-cigarette smoking":ti,ab OR "electronic cigarette smoking":ti,ab OR vaping:ti,ab OR vape*:ti,ab OR cigar*:ti,ab OR "Tobacco, Waterpipe":MH OR "Water Pipe Smoking":MH OR "Smoking Water Pipes":MH OR argile:ti,ab OR goza:ti,ab OR hookah:ti,ab OR narghile:ti,ab OR shisha:ti,ab OR "smoking water pipe":ti,ab OR "smoking water pipes":ti,ab

#39 "Nitrous Oxide":MH OR "dinitrogen monoxide":ti,ab OR "dinitrogen oxide":ti,ab OR "factitious air":ti,ab OR "hyponitrous acid anhydride":ti,ab OR lachgas:ti,ab OR "laughing gas":ti,ab OR "nitrogen hypoxide":ti,ab OR "nitrogen protoxide":ti,ab OR "nitrous oxide":ti,ab OR whippet*:ti,ab OR nangs:ti,ab OR "buzz bomb*":ti,ab OR "hippy crack":ti,ab

#40 #1 OR #2 OR #3 OR #4 OR #5 OR #6 OR #7 OR #8 OR #9 OR #10 OR #11 OR #12 OR #13 OR #14 OR #15 OR #16 OR #17 OR #18 OR #19 OR #20 OR #21 OR #22 OR #23 OR #24 OR #25 OR #26 OR #27 OR #28 OR #29 OR #30 OR #31 OR #32 OR #33 OR #34 OR #35 OR #36 OR #37 OR #38 OR #39

#41 "text analytic*":ti,ab OR "text information extraction":ti,ab OR "named entity extraction":ti,ab OR "named entity recognition":ti,ab OR "co-reference resolution":ti,ab OR "relation extraction":ti,ab OR "Sentiment Analysis":MH OR "emotion ai":ti,ab OR "opinion mining":ti,ab OR "sentiment analysis":ti,ab OR "topic modeling":ti,ab OR "word embedding":ti,ab

#42 "language model*":ti,ab OR "large language model*":ti,ab OR "generative pre-trained transformer":ti,ab OR "generative pre-training transformer":ti,ab OR "generative pretrained transformer":ti,ab OR "transformer model*":ti,ab OR "bidirectional encoder representations from transformer*":ti,ab OR "few shot learning":ti,ab OR "zero shot learning":ti,ab OR "prompt engineering":ti,ab OR "text classification*":ti,ab OR "Word Processing":MH OR "text processing":ti,ab OR "word processing":ti,ab OR "syntactic parsing":ti,ab OR "semantic analysis":ti,ab OR "semantic analytic*":ti,ab OR "discourse analysis":ti,ab OR "text summarization":ti,ab

#43 "Neural Networks, Computer":MH OR "mlp multilayer perceptron":ti,ab OR "mlp neural network":ti,ab OR "multi-layer perceptron":ti,ab OR "multilayer perceptron":ti,ab OR "multilayer perceptron network":ti,ab OR "multilayer perceptron neural network":ti,ab OR "multiple layer perceptron":ti,ab OR "cnn convolutional neural network":ti,ab OR "cnns convolutional neural networks":ti,ab OR convnet:ti,ab OR "convoluted neural network":ti,ab OR "convolution neural network":ti,ab OR "convolutional anns":ti,ab OR "convolutional nn":ti,ab OR "convolutional artificial neural network":ti,ab OR "convolutional deep neural network":ti,ab OR "convolutional neural network":ti,ab OR "deep convolutional neural network":ti,ab OR "recursive neural network":ti,ab OR "rnn recurrent neural network":ti,ab OR "rnns recurrent neural networks":ti,ab OR "recurrent ann":ti,ab OR "recurrent nn":ti,ab OR "recurrent nns":ti,ab OR "recurrent artificial neural network":ti,ab OR "recurrent neural network":ti,ab OR "lstm model":ti,ab OR "lstm network":ti,ab OR "lstm neural network":ti,ab OR "lstm recurrent neural network":ti,ab OR "lstm-rnn":ti,ab OR "lstm-rnns":ti,ab OR "rnn-lstm":ti,ab OR "long short term memory lstm network":ti,ab OR "long short term memory lstm neural network":ti,ab OR "long short term memory neural network":ti,ab OR "long short term memory network":ti,ab OR "long short-term memory recurrent neural network":ti,ab OR "sequence to sequence model*":ti,ab OR "shallow neural network*":ti,ab OR "ann artificial neural network":ti,ab OR "ann analysis":ti,ab OR "ann approach":ti,ab OR "ann method":ti,ab OR "ann methodology":ti,ab OR "ann methods":ti,ab OR "ann model":ti,ab OR "ann modeling":ti,ab OR "ann modelling":ti,ab OR "ann models":ti,ab OR "ann output":ti,ab OR "ann technique":ti,ab OR "ann techniques":ti,ab OR "ann training":ti,ab OR "anns artificial neural networks":ti,ab OR "artificial nn":ti,ab OR "artificial nns":ti,ab OR "artificial neural network":ti,ab OR "artificial neural networks":ti,ab OR "computational neural network":ti,ab OR "computer neural network":ti,ab OR "computer neural networks":ti,ab OR "connectionist model":ti,ab OR "connectionist network":ti,ab OR "connectionist neural network":ti,ab OR "connectionist system":ti,ab OR "mathematical neural network":ti,ab OR "neural network computer":ti,ab OR "neural network algorithm":ti,ab OR "neural network model":ti,ab OR "neural networks computer":ti,ab OR "clinical note*":ti,ab OR "free text*":ti,ab

#44 "Natural Language Processing":MH OR "natural language processing":ti,ab OR "text mining":ti,ab OR "text mine*":ti,ab

#45 #41 OR #42 OR #43 OR #44

#46 "Electronic Health Records":MH OR "ehr electronic health record":ti,ab OR "electronic health record":ti,ab OR "electronic health records":ti,ab OR "electronic healthcare database":ti,ab OR "electronic medical record":ti,ab OR "Telemedicine":MH OR "e-health":ti,ab OR ehealth:ti,ab OR "tele-health":ti,ab OR telehealth:ti,ab OR "tele medicine":ti,ab OR telemedicine:ti,ab OR "virtual medicine":ti,ab OR "m health":ti,ab OR "e visit*":ti,ab

#47 #40 AND #45 AND #46

#48 #40 AND #45 AND #46 with Cochrane Library publication type restrictions for English language

EMBASE

1. exp opioid analgesic agent/ or algopan.ti,ab. or biopon.ti,ab. or laudanum.ti,ab. or nepenthe.ti,ab. or omnopon.ti,ab. or opial.ti,ab. or opiate\$.ti,ab. or (opiate adj2 alkaloid\$).ti,ab. or opioid\$.ti,ab. or opium.ti,ab. or (opium adj2 alkaloid\$).ti,ab. or (opium adj2 derivative\$).ti,ab. or (opium adj poppy).ti,ab. or (opium adj tincture).ti,ab. or opon.ti,ab. or pantopon.ti,ab. or papaveretum.ti,ab. or pavon.ti,ab. or tetrapon.ti,ab.

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2. exp heroin/ or acetomorphine.ti,ab. or (diacetyl adj morphine).ti,ab. or diacetylmorphine.ti,ab. or (diacetylmorphine adj hydrochloride).ti,ab. or diamorphine.ti,ab. or (diamorphine adj hydrochloride).ti,ab. or diaphorin.ti,ab. or heroin.ti,ab. or (heroin adj hydrochloride).ti,ab. or heroine.ti,ab. or morphacetin.ti,ab.
3. exp oxycodone/ or alivio.ti,ab. or bionone.ti,ab. or (col adj2 003).ti,ab. or col003.ti,ab. or dihydrohydroxycodone.ti,ab. or dihydrone.ti,ab. or endone.ti,ab. or eubine.ti,ab. or eucodal.ti,ab. or eucodolum.ti,ab. or eukodal.ti,ab. or nargenol.ti,ab. or (nsc adj2 19043).ti,ab. or opton.ti,ab. or ossicodone.ti,ab. or oxanest.ti,ab. or oxaydo.ti,ab. or oxecta.ti,ab. or oxiconona.ti,ab. or oxicone.ti,ab. or (oxy adj ir).ti,ab. or oxycodon.ti,ab. or oxycodone.ti,ab. or (oxycodone adj2 (hcl or hydrochloride)).ti,ab. or oxycone.ti,ab. or oxycontin.ti,ab. or (oxycontin adj neo).ti,ab. or oxydol.ti,ab. or oxyfast.ti,ab. or oxygesic.ti,ab. or oxyir.ti,ab. or oxylan.ti,ab. or oxyneo.ti,ab. or oxynorm.ti,ab. or oxypro.ti,ab. or pavinal.ti,ab. or pronarcin.ti,ab. or (pti adj2 821).ti,ab. or pti821.ti,ab. or remoxy.ti,ab. or roxicodone.ti,ab. or roxybond.ti,ab. or xtampza.ti,ab. or (xtampza adj er).ti,ab.
4. exp hydrocodone/ or bekadid.ti,ab. or dico.ti,ab. or dicodid.ti,ab. or dihydrocodeinone.ti,ab. or hydrocodone.ti,ab. or hydrocodonum.ti,ab.
5. exp fentanyl/ or (ap adj2 48).ti,ab. or ap48.ti,ab. or (az adj2 003).ti,ab. or az003.ti,ab. or duragesic\$.ti,ab. or durogesic.ti,ab. or durotep.ti,ab. or fentamyl.ti,ab. or fentanil.ti,ab. or fentanyl.ti,ab. or (fentanyl adj3 (buccal or soluble or film or hydrochloride or iontophoretic)).ti,ab. or jns020qd.ti,ab. or leptanal.ti,ab. or matrifen.ti,ab. or pecfent.ti,ab. or phentanyl.ti,ab. or (r adj2 4263).ti,ab. or r4263.ti,ab. or recuvyra.ti,ab. or subsys.ti,ab. or tanyl.ti,ab.
6. exp morphine/ or anpec.ti,ab. or duromorph.ti,ab. or epimorph.ti,ab. or miro.ti,ab. or morfin.ti,ab. or morfine.ti,ab. or morphia.ti,ab. or morphin.ti,ab. or morphine.ti,ab. or (morphine adj3 (alkaloid or chlorhydrate or chloride or hydrochloride or suspension)).ti,ab. or morphinium.ti,ab. or morphium.ti,ab. or opso.ti,ab. or skenan.ti,ab. or (trans adj morphine).ti,ab.
7. exp codeine/ or codein.ti,ab. or codeine.ti,ab. or codipertussin.ti,ab. or codyl.ti,ab. or (methyl adj morphine).ti,ab. or methylmorphine.ti,ab. or (morphine adj2 (3 adj methyl adj ether)).ti,ab. or (morphine adj2 monomethyl adj2 ether).ti,ab. or (trans adj codeine).ti,ab.
8. exp methadone/ or adanon.ti,ab. or algolysin.ti,ab. or algovetin.ti,ab. or amidon.ti,ab. or amidone.ti,ab. or (an adj2 148).ti,ab. or an148.ti,ab. or anadon.ti,ab. or butalgin.ti,ab. or deamin.ti,ab. or deprimol.ti,ab. or diaminon.ti,ab. or dolamid.ti,ab. or dolmed.ti,ab. or dolophin.ti,ab. or dolophine.ti,ab. or dorex.ti,ab. or eptadone.ti,ab. or fenadon.ti,ab. or heptadon.ti,ab. or heptadone.ti,ab. or heptanon.ti,ab. or ketalgin.ti,ab. or l-polamidon.ti,ab. or mecodin.ti,ab. or metadol.ti,ab. or metadon.ti,ab. or methaddict.ti,ab. or methadon.ti,ab. or methadone.ti,ab. or (methadone adj2 (base or hydrochloride)).ti,ab. or methadose.ti,ab. or miadone.ti,ab. or phenadon.ti,ab. or physeptone.ti,ab. or polamidon.ti,ab. or polamivet.ti,ab. or sedo-rapide.ti,ab. or symoron.ti,ab. or win.ti,ab.
9. exp buprenorphine/ or addnok.ti,ab. or astec.ti,ab. or belbuca.ti,ab. or brixadi.ti,ab. or buprenex.ti,ab. or buprenorfin.ti,ab. or buprenorfinna.ti,ab. or buprenorfine.ti,ab. or buprenorphin.ti,ab. or buprenorphine.ti,ab. or (buprenorphine adj2 hydrochloride).ti,ab. or butec.ti,ab. or butrans.ti,ab. or buvidal.ti,ab. or cam2038.ti,ab. or lepetan.ti,ab. or (lyn adj2 013).ti,ab. or lyn013.ti,ab. or norphin.ti,ab. or norspan.ti,ab. or probuphenine.ti,ab. or probuphine.ti,ab. or (rbp adj2 6000).ti,ab. or rbp6000.ti,ab. or sixmo.ti,ab. or sublocade.ti,ab. or subutex.ti,ab. or temgesic.ti,ab. or transtec.ti,ab.
10. exp tramadol/ or ad2112.ti,ab. or adamon.ti,ab. or adolonta.ti,ab. or amanda.ti,ab. or analab.ti,ab. or andalpha.ti,ab. or bio301.ti,ab. or calmol.ti,ab. or (cg adj2 (315 or 315e)).ti,ab. or cg315.ti,ab. or contramal.ti,ab. or conzip.ti,ab. or dolzam.ti,ab. or (e adj2 (381 or 382)).ti,ab. or e381.ti,ab. or e382.ti,ab. or marol.ti,ab. or monocrixo.ti,ab. or noax.ti,ab. or nobligan.ti,ab. or (ns adj2 24).ti,ab. or ns24.ti,ab. or prontalgin.ti,ab. or qdolo.ti,ab. or ralivia.ti,ab. or ryzolt.ti,ab. or t-long.ti,ab. or tioner.ti,ab. or tiparol.ti,ab. or topalgic.ti,ab. or (topalgic adj lp).ti,ab. or toram.ti,ab. or tradolan.ti,ab. or tradonal.ti,ab. or tralgit.ti,ab. or tramadol.ti,ab. or (tramadol adj2 (hcl or hydrochloride or lp or retard or sr)).ti,ab. or
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tramadolis.ti,ab. or tramadolo.ti,ab. or tramadolor.ti,ab. or tramal.ti,ab. or tramazac.ti,ab. or tramol.ti,ab. or tramundin.ti,ab. or tridol.ti,ab. or tridural.ti,ab. or trodon.ti,ab. or ultram.ti,ab. or (ultram adj er).ti,ab. or zamadol.ti,ab. or zertane.ti,ab. or zydol.ti,ab. or (zydol adj sr).ti,ab. or zytram.ti,ab.

11. exp hydromorphone/ or dihydromorphinone.ti,ab. or dihydromorphone.ti,ab. or dilaudid.ti,ab. or dimorphone.ti,ab. or exalgo.ti,ab. or (hydromorph adj contin).ti,ab. or hydromorphon.ti,ab. or hydromorphone.ti,ab. or (hydromorphone adj2 hydrochloride).ti,ab. or jornista.ti,ab. or novolaudon.ti,ab. or palladon.ti,ab. or palladone.ti,ab.

12. exp oxymorphone/ or hydroxydihydromorphinone.ti,ab. or numorphan.ti,ab. or opana.ti,ab. or (opana adj er).ti,ab. or oxymorphone.ti,ab. or (oxymorphone adj2 hydrochloride).ti,ab.

13. exp cannabinoid/ or exp cannabis/ or cannabinoid\$.ti,ab. or (cannabis adj3 (sativa adj (extract or resin))).ti,ab. or bhang.ti,ab. or cannabis.ti,ab. or (cannabis adj2 (constituent or extract or leaf)).ti,ab. or cannador.ti,ab. or charas.ti,ab. or ganja.ti,ab. or hashish.ti,ab. or (hashish adj oil).ti,ab. or (hemp adj extract).ti,ab. or marihuana.ti,ab. or marijuana.ti,ab. or exp medical marijuana/ or (medical adj (cannabis or marihuana or marijuana)).ti,ab. or (medicinal adj (cannabis or marijuana)).ti,ab. or (marijuana adj treatment).ti,ab. or exp dronabinol/ or ((1 adj trans adj delta adj2 9) adj tetrahydrocannabinol).ti,ab. or (delta adj2 (1 or 9) adj2 (trans adj tetrahydrocannabinol or tetrahydrocannabinol)).ti,ab. or (delta1 adj2 (tetrahydrocannabinol or thc or trans adj tetrahydrocannabinol)).ti,ab. or (delta9 adj2 (tetrahydro adj cannabinol or tetrahydrocannabinol or trans adj tetrahydrocannabinol)).ti,ab. or dronabinol.ti,ab. or (1 adj delta adj2 9 adj trans adj tetrahydrocannabinol).ti,ab. or marinol.ti,ab. or (qcd adj2 84924).ti,ab. or syndros.ti,ab. or (tetrahydrocannabinol adj delta9).ti,ab. or (trans adj delta adj2 9 adj tetrahydrocannabinol).ti,ab. or thc.ti,ab. or (delta adj2 3 adj tetrahydrocannabinol).ti,ab. or (delta adj tetrahydrocannabinol).ti,ab. or (delta3 adj tetrahydrocannabinol).ti,ab. or (sp adj2 104).ti,ab. or (tetrahydro adj cannabinol).ti,ab. or tetrahydrocannabinol.ti,ab. or tetrahydrocannabinol.ti,ab. or tetrahydrocannabinol.ti,ab. or (trans adj tetrahydrocannabinol).ti,ab. or scb.ti,ab.

14. exp ethanol/ or alcohol.ti,ab. or ethanol.ti,ab. or ethylalcohol.ti,ab.

15. exp alcoholic beverage/ or exp absinthe/ or exp beer/ or exp wine/ or (alcoholic adj (beverage\$ or drink\$)).ti,ab. or (liquor adj alcohol).ti,ab. or absinthe.ti,ab. or beer.ti,ab. or brandy.ti,ab. or gin.ti,ab. or makgeolli.ti,ab. or makkoli.ti,ab. or makoli.ti,ab. or (honey adj wine).ti,ab. or pulque.ti,ab. or rum.ti,ab. or (rice adj wine).ti,ab. or sake.ti,ab. or vodka.ti,ab. or bourbon.ti,ab. or (bourbon adj whiskey).ti,ab. or (scotch adj whiskey).ti,ab. or whiskey.ti,ab. or whisky.ti,ab. or wine.ti,ab. or (apple adj (cider or wine)).ti,ab. or cider.ti,ab.

16. exp benzodiazepine derivative/ or benzodiazepine\$.ti,ab.

17. exp barbiturate derivative/ or barbiturate\$.ti,ab. or (barbiturate adj derivative\$.ti,ab. or (barbituric adj acid adj derivative\$).ti,ab.

18. exp gamma hydroxybutyric acid/ or ghba.ti,ab. or (gamma adj (hydroxy adj butyric adj acid or hydroxybutyrate or hydroxybutyric adj acid)).ti,ab.

19. exp hallucinogen/ or hallucinogen\$.ti,ab. or hallucinogenic.ti,ab. or (hallucinogenic adj (agent or drug\$)).ti,ab. or psychedelia.ti,ab. or psychedelic\$.ti,ab. or (psychedelic adj (agent\$ or drug\$)).ti,ab. or psychodelic\$.ti,ab. or psychodysleptic.ti,ab. or (psychodysleptic adj drug).ti,ab. or psychomimetic.ti,ab. or (psychomimetic adj drug).ti,ab. or (psychotic adj drug).ti,ab. or psychotomimetic.ti,ab. or (psychotomimetic adj (agent or drug\$)).ti,ab.

20. exp lysergide/ or lsd.ti,ab. or delysid.ti,ab. or (l adj s adj d).ti,ab. or (lsd adj2 25).ti,ab. or (lysergic adj acid adj diethylamide).ti,ab. or lysergide.ti,ab.

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21. exp 3,4-methylenedioxymethamphetamine/ or mdma.ti,ab. or ecstasy.ti,ab. or methylenedioxymethamphetamine.ti,ab. or midomafetamine.ti,ab.
22. exp phencyclidine/ or (angel adj dust).ti,ab. or (ci adj2 395).ti,ab. or ci395.ti,ab. or (cl adj2 395).ti,ab. or (gp adj2 121).ti,ab. or phencyclidin.ti,ab. or phencyclidine.ti,ab. or (phencyclidine adj2 hydrochloride).ti,ab. or phenycyclidine.ti,ab. or phenylcyclidine.ti,ab. or sernyl.ti,ab. or sernylan.ti,ab.
23. exp psilocybine/ or comp360.ti,ab. or (cy adj2 39).ti,ab. or indocybin.ti,ab. or psilocybin.ti,ab. or psilocybine.ti,ab.
24. exp mescaline/ or mescaline.ti,ab. or mescaline.ti,ab. or (mescaline adj2 hydrochloride).ti,ab. or mezcaine.ti,ab. or peyote.ti,ab. or peyotine.ti,ab. or peyotl.ti,ab.
25. exp ketamine/ or calipsol.ti,ab. or calypsol.ti,ab. or (ci adj2 581).ti,ab. or ci581.ti,ab. or imalgene.ti,ab. or kalipsol.ti,ab. or katamine.ti,ab. or ketaject.ti,ab. or ketalar.ti,ab. or ketamine.ti,ab. or (ketamine adj2 (hcl or hydrochloride)).ti,ab. or ketanest.ti,ab. or ketased.ti,ab. or ketaset.ti,ab. or ketavet.ti,ab. or ketolar.ti,ab. or narkamon.ti,ab. or (sls adj2 002).ti,ab. or sls002.ti,ab. or tekam.ti,ab. or velonarcon.ti,ab. or vetalar.ti,ab.
26. exp dimethyltryptamine/ or (dimethyl adj tryptamine).ti,ab. or dimethyltryptamine.ti,ab. or (n adj dimethyltryptamine).ti,ab. or (n adj n adj dimethyltryptamine).ti,ab.
27. exp central stimulant agent/ or analeptic\$.ti,ab. or (analeptic adj (agent\$ or drug\$)).ti,ab. or (psychoanaleptic adj agent).ti,ab. or stimulant\$.ti,ab. or (stimulating adj agent\$).ti,ab. or (stimulative adj agent\$).ti,ab.
28. exp cocaine/ or exp crack cocaine/ or (beta adj cocaine).ti,ab. or cocain.ti,ab. or (cocain adj hydrochloride).ti,ab. or cocaine.ti,ab. or (cocaine adj2 (hydrochloride or methiodide)).ti,ab. or (crack adj cocaine).ti,ab. or (ecgonine adj methyl adj ester adj benzoate).ti,ab. or (l adj cocaine).ti,ab. or neurocaine.ti,ab.
29. exp methamphetamine/ or adipex.ti,ab. or ambar.ti,ab. or corvitin.ti,ab. or deoxyephedrine.ti,ab. or desamine.ti,ab. or desoxyephedrine.ti,ab. or (desoxyephedrine adj2 hydrochloride).ti,ab. or desoxyn.ti,ab. or desyphed.ti,ab. or detrex.ti,ab. or (dl adj methamphetamine).ti,ab. or doe.ti,ab. or gerovit.ti,ab. or hiropon.ti,ab. or isophen.ti,ab. or (l adj methamphetamine).ti,ab. or metamfetamine.ti,ab. or metamphetamine.ti,ab. or methamine.ti,ab. or methamphetamin.ti,ab. or methamphetamine.ti,ab. or (methamphetamine adj2 (hcl or hydrochloride)).ti,ab. or methedrine.ti,ab. or methoxyn.ti,ab. or (methyl adj amphetamine).ti,ab. or methylamphetamine.ti,ab. or (methylamphetamine adj2 hydrochloride).ti,ab. or (n adj methylamphetamine).ti,ab. or norodin.ti,ab. or pervitin.ti,ab. or philopon.ti,ab.
30. exp amphetamine/ or actedron.ti,ab. or adipan.ti,ab. or adzenys.ti,ab. or (adzenys adj er).ti,ab. or aktedrin.ti,ab. or aktedron.ti,ab. or alentol.ti,ab. or allodene.ti,ab. or (alpha adj (amphetamine or methylphenethylamine or methylphenylethylamine)).ti,ab. or amfetamine.ti,ab. or amphamed.ti,ab. or amphamine.ti,ab. or amphetaime.ti,ab. or amphetamin.ti,ab. or amphetamine.ti,ab. or (amphetamine adj2 (detection or hydrochloride or intoxication or metabolism or resin adj complex or sulfate or sulphate or toxicity)).ti,ab. or amphethamine.ti,ab. or amphezamin.ti,ab. or anara.ti,ab. or (ar adj2 19).ti,ab. or ar19.ti,ab. or astedin.ti,ab. or benzafinyl.ti,ab. or benzebar.ti,ab. or benzedrine.ti,ab. or benzolone.ti,ab. or benzpropamine.ti,ab. or (beta adj (aminopropylbenzene or phenyl adj isopropylamine or phenylisopropylamine)).ti,ab. or betafen.ti,ab. or bluzedrin.ti,ab. or centramina.ti,ab. or centramine.ti,ab. or (d adj l adj amphetamine).ti,ab. or (delta adj amphetamine).ti,ab. or diethamine.ti,ab. or dipan.ti,ab. or elastonin.ti,ab. or elastonon.ti,ab. or euphobine.ti,ab. or euphohne.ti,ab. or euphodyn.ti,ab. or evekeo.ti,ab. or (evekeo adj odt).ti,ab. or fabedrine.ti,ab. or fenara.ti,ab. or fenedrin.ti,ab. or ibiozedrine.ti,ab. or isoamin.ti,ab. or isoamine.ti,ab. or isoamyne.ti,ab. or isomyn.ti,ab. or (l adj amphetamine).ti,ab. or levamfetamine.ti,ab. or (levo adj amphetamine).ti,ab. or levoamphetamine.ti,ab. or
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linampheta.ti,ab. or mecodrin.ti,ab. or mimetina.ti,ab. or monophos.ti,ab. or noclon.ti,ab. or norephedrane.ti,ab. or norphedrane.ti,ab. or novydrine.ti,ab. or (nt adj2 0201).ti,ab. or obetrol.ti,ab. or oktedrin.ti,ab. or oraldrina.ti,ab. or ortedrine.ti,ab. or percomon.ti,ab. or pharmamedrine.ti,ab. or pharmedrine.ti,ab. or phenamin.ti,ab. or phenedrine.ti,ab. or phenpromin.ti,ab. or (phenyl adj isopropylamine).ti,ab. or phenylaminopropane.ti,ab. or profamina.ti,ab. or profetamine.ti,ab. or propisamine.ti,ab. or psychedrin.ti,ab. or psychedrine.ti,ab. or psychoton.ti,ab. or racephen.ti,ab. or raphetamine.ti,ab. or rhinalator.ti,ab. or sedolin.ti,ab. or simpamina.ti,ab. or simpamine.ti,ab. or simpatedrin.ti,ab. or sympametin.ti,ab. or sympamine.ti,ab. or sympatedrine.ti,ab. or theptine.ti,ab. or vapedrine.ti,ab. or zedrine.ti,ab.

31. exp drug dependence/ or exp alcoholism/ or exp binge drinking/ or exp student drinking/ or exp driving under the influence/ or exp drug misuse/ or exp prescription drug misuse/ or exp inhalant abuse/ or (substance adj (usage or use)).ti,ab. or addict.ti,ab. or (addiction adj drug).ti,ab. or (dependence adj drug).ti,ab. or (drug adj (addict or addiction or dependence or dependency or facilitation or habituation)).ti,ab. or (physical adj dependence).ti,ab. or (substance adj (addiction or dependence or dependency or use adj disorder\$)).ti,ab. or (substance-related adj disorder\$).ti,ab. or toxicomania\$.ti,ab. or toxicomanie.ti,ab. or (abuse adj (drug or alcohol)).ti,ab. or (drug adj (abuse or abuser or problem)).ti,ab. or (alcohol adj abuse).ti,ab. or (ethanol adj abuse).ti,ab. or (binge adj drinking).ti,ab. or (heavy adj episodic adj drinking).ti,ab. or (alcohol adj drinking adj in adj college).ti,ab. or (college adj (alcohol adj use or drinking or student adj drinking)).ti,ab. or (student adj drinking).ti,ab. or (university adj student adj drinking).ti,ab. or (driving adj under adj the adj influence).ti,ab. or (driving adj drunken).ti,ab. or (drunk\$ adj driv\$).ti,ab. or (excessive or hazardous or heavy or problem\$ or problematic) adj drinking).ti,ab. or (addiction adj alcohol).ti,ab. or (alcohol adj (addiction or dependence or dependency or dependents or polyneuropathy or use adj disorder or dependent adj individual)).ti,ab. or (alcohol-induced adj disorders).ti,ab. or (alcohol-related adj disorders).ti,ab. or alcoholic\$.ti,ab. or (alcoholic adj (individual or neuropathy or polyneuritis or polyneuropathy)).ti,ab. or alcoholism.ti,ab. or (chronic adj alcoholism).ti,ab. or (dependence adj alcohol).ti,ab. or dipsomania\$.ti,ab. or (ethanol adj dependence).ti,ab. or (drug adj misuse).ti,ab. or (medicine adj misuse).ti,ab. or nmupd.ti,ab. or (medication adj misuse).ti,ab. or (non-medical adj use adj of adj prescription adj drugs).ti,ab. or (nonmedical adj use adj of adj prescription adj drugs).ti,ab. or (prescription adj (drug or medication or medicine) adj misuse).ti,ab. or (glue adj sniffing).ti,ab. or (sniffing adj glue).ti,ab.

32. exp narcotic agent/ or (narcotic adj (agent\$ or drug\$ or plant)).ti,ab. or narcotic\$.ti,ab. or stupefacient.ti,ab.

33. addiction\$.ti,ab. or (addictive adj (behavior\$ or behaviour\$ or disorder\$)).ti,ab. or addictive.ti,ab. or addict\$.ti,ab. or (behavior adj addictive).ti,ab. or (behaviour adj addictive).ti,ab. or (chemical adj dependence).ti,ab.

34. exp street drug/ or (illegal adj drug\$).ti,ab. or (illicit adj drug\$).ti,ab.

35. (multi-drug or multidrug or multiple adj drug or poly-drug or polydrug) adj (abuse or addiction or use).ti,ab. or (multiple adj addiction).ti,ab.

36. exp inhalational drug abuse/ or (inhalant\$ adj abuse).ti,ab. or (inhalation\$ adj (abuse or drug adj abuse)).ti,ab.

37. exp designer drug/ or (designer adj drug\$).ti,ab. or exp controlled drug/ or (controlled adj (drug\$ or medicine\$ or substance\$)).ti,ab. or exp tobacco product/ or exp tobacco use/ or tobacco.ti,ab. or exp nicotine/ or (beta adj pyridyl adj alpha adj n adj methylpyrrolidine).ti,ab. or habitrol.ti,ab. or nicabate.ti,ab. or nicoderm.ti,ab. or (nicoderm adj cq).ti,ab. or nicolan.ti,ab. or nicopatch.ti,ab. or nicotin.ti,ab. or nicotine.ti,ab. or (nicotine adj tts).ti,ab. or nicotinell.ti,ab. or (nicotinell adj (lozenge or tts)).ti,ab. or nicotrol.ti,ab. or (nicotrol adj (inhaler or ns)).ti,ab. or niquitin.ti,ab. or (niquitin adj cq).ti,ab. or prostep.ti,ab. or (x adj2 22).ti,ab. or x22.ti,ab.

38. exp designer drug/ or (designer adj drug\$).ti,ab. or exp controlled drug/ or (controlled adj (drug\$ or medicine\$ or substance\$)).ti,ab. or tobacco.ti,ab. or exp nicotine/ or (beta adj pyridyl adj alpha adj n adj methylpyrrolidine).ti,ab. or habitrol.ti,ab. or nicabate.ti,ab. or nicoderm.ti,ab. or (nicoderm adj cq).ti,ab. or nicolan.ti,ab. or nicopatch.ti,ab. or nicotin.ti,ab. or nicotine.ti,ab. or (nicotine adj tts).ti,ab. or nicotinell.ti,ab. or (nicotinell adj (lozenge or tts)).ti,ab. or nicotrol.ti,ab. or (nicotrol adj (inhaler or ns)).ti,ab. or niquitin.ti,ab. or (niquitin adj cq).ti,ab. or

prostep.ti,ab. or (x adj2 22).ti,ab. or x22.ti,ab. or exp smoking/ or (behavior adj smoking).ti,ab. or (behaviour adj smoking).ti,ab. or (reverse adj smoking).ti,ab. or smoker\$.ti,ab. or smoking.ti,ab. or (smoking adj (behavior or behaviour)).ti,ab. or (tobacco adj smoking).ti,ab. or exp cigarette smoking/ or exp vaping/ or exp electronic cigarette/ or cigarette\$.ti,ab. or (filter adj cigarette).ti,ab. or (e adj cigarette\$.ti,ab. or (electronic adj cigarette\$.ti,ab. or (electronic adj nicotine adj delivery adj system\$.ti,ab. or (e-cigarette adj smoking).ti,ab. or (electronic adj cigarette adj smoking).ti,ab. or vaping.ti,ab. or vape\$.ti,ab. or cigar\$.ti,ab. or exp waterpipe/ or exp waterpipe smoking/ or argghile.ti,ab. or goza.ti,ab. or hookah.ti,ab. or narghile.ti,ab. or shisha.ti,ab. or (smoking adj water adj pipe\$.ti,ab.

39. exp nitrous oxide/ or (dinitrogen adj (monoxide or oxide)).ti,ab. or (factitious adj air).ti,ab. or (hyponitrous adj acid adj anhydride).ti,ab. or lachgas.ti,ab. or (laughing adj gas).ti,ab. or (nitrogen adj (hypoxide or protoxide)).ti,ab. or (nitrous adj oxide).ti,ab. or whippet\$.ti,ab. or nangs.ti,ab. or (buzz adj bomb\$.ti,ab. or (hippy adj crack).ti,ab.

40. 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39

41. (text adj analytic\$.ti,ab. or (text adj information adj extraction).ti,ab. or (named adj entity adj (extraction or recognition)).ti,ab. or (co-reference adj resolution).ti,ab. or (relation adj extraction).ti,ab. or exp sentiment analysis/ or (emotion adj ai).ti,ab. or (opinion adj mining).ti,ab. or (sentiment adj analysis).ti,ab. or (topic adj modeling).ti,ab. or (word adj embedding).ti,ab.

42. (language adj model\$.ti,ab. or (large adj language adj model\$.ti,ab. or (generative adj (pre-trained or pre-training or pretrained) adj transformer).ti,ab. or (transformer adj model\$.ti,ab. or (bidirectional adj encoder adj representations adj from adj transformer\$.ti,ab. or (few adj shot adj learning).ti,ab. or (zero adj shot adj learning).ti,ab. or (prompt adj engineering).ti,ab. or (text adj classification\$.ti,ab. or exp word processing/ or (text adj processing).ti,ab. or (word adj processing).ti,ab. or (syntactic adj parsing).ti,ab. or (semantic adj (analysis or analytic\$)).ti,ab. or (discourse adj analysis).ti,ab. or (text adj summarization).ti,ab.

43. exp artificial neural network/ or (mlp adj (multilayer adj perceptron or neural adj network)).ti,ab. or (multi-layer adj perceptron).ti,ab. or (multilayer adj perceptron adj (network or neural adj network)).ti,ab. or (multiple adj layer adj perceptron).ti,ab. or (cnn adj convolutional adj neural adj network\$.ti,ab. or convnet.ti,ab. or (convolut\$ adj (neural adj network or anns or nn or artificial adj neural adj network or deep adj neural adj network)).ti,ab. or (deep adj convolutional adj neural adj network).ti,ab. or (recursive adj neural adj network).ti,ab. or (rnn adj recurrent adj neural adj network\$.ti,ab. or (recurrent adj (ann or nn\$ or artificial adj neural adj network or neural adj network)).ti,ab. or (lstm adj (model or network or neural adj network or recurrent adj neural adj network or -rnn\$)).ti,ab. or (rnn-lstm).ti,ab. or (long adj short adj term adj memory adj (lstm adj (network or neural adj network) or network or recurrent adj neural adj network)).ti,ab. or (long adj short-term adj memory adj recurrent adj neural adj network).ti,ab. or (sequence adj to adj sequence adj model\$.ti,ab. or (shallow adj neural adj network\$.ti,ab. or (ann adj (artificial adj neural adj network or analysis or approach or method\$ or model\$ or output or technique\$ or training)).ti,ab. or (anns adj artificial adj neural adj networks).ti,ab. or (artificial adj nn\$).ti,ab. or (artificial adj neural adj network\$.ti,ab. or (computational adj neural adj network).ti,ab. or (computer adj neural adj network\$.ti,ab. or (connectionist adj (model or network or neural adj network or system)).ti,ab. or (mathematical adj neural adj network).ti,ab. or (neural adj network adj (computer or algorithm or model)).ti,ab. or (neural adj networks adj computer).ti,ab. or (clinical adj note\$.ti,ab. or (free adj text\$.ti,ab.

44. exp natural language processing/ or (natural adj language adj processing).ti,ab. or (text adj mining).ti,ab. or (text adj mine\$.ti,ab.

45. 41 or 42 or 43 or 44

	46. exp electronic health record/ or (ehr adj electronic adj health adj record).ti,ab. or (electronic adj (health adj record\$ or healthcare adj database or medical adj record)).ti,ab. or exp telemedicine/ or e-health.ti,ab. or ehealth.ti,ab. or tele-health.ti,ab. or telehealth.ti,ab. or (tele adj medicine).ti,ab. or telemedicine.ti,ab. or (virtual adj medicine).ti,ab. or (m adj health).ti,ab. or (e adj visit\$).ti,ab. 47. 40 and 45 and 46 48. limit 47 to english 49. limit 47 to (english language and yr="2000-current")
WEB OF SCIENCE	#1 TS=(opiate* OR opioid* OR algonan OR biopon OR laudanum OR nepenthe OR omnopon OR opial OR "opiate alkaloid*" OR "opium alkaloid*" OR opium OR "opium derivative*" OR "opium poppy" OR "opium tincture" OR opon OR pantopon OR papaveretum OR pavon OR tetrapon) #2 TS=(heroin OR acetomorphine OR "diacetyl morphine" OR diacetylmorphine OR "diacetylmorphine hydrochloride" OR diamorphine OR "diamorphine hydrochloride" OR diaphorin OR "heroin hydrochloride" OR heroine OR morphacetin) #3 TS=(oxycodone OR alivio OR bionone OR "col 003" OR col003 OR dihydrohydroxycodone OR dihydron OR endone OR eubine OR eucodal OR eucodalum OR eukodal OR nargenol OR "nsc 19043" OR opton OR ossicodone OR oxanest OR oxaydo OR oxepta OR oxicodona OR oxicone OR "oxy ir" OR oxycodon OR "oxycodone hcl" OR "oxycodone hydrochloride" OR oxycone OR oxycontin OR "oxycontin neo" OR oxydol OR oxyfast OR oxygesic OR oxyir OR oxylan OR oxyneo OR oxynorm OR oxypro OR pavinal OR pronarcin OR "pti 821" OR pti821 OR remoxy OR roxicodone OR roxybond OR xtampza OR "xtampza er") #4 TS=(hydrocodone OR bekadid OR dico OR dicodid OR dihydrocodeinone OR hydrocodonum) #5 TS=(fentanyl OR "ap 48" OR ap48 OR "az 003" OR az003 OR duragesic* OR durogesic OR durotep OR fentamyl OR fentanil OR "fentanyl buccal soluble film" OR "fentanyl hydrochloride" OR "fentanyl iontophoretic" OR "fentanyl-100" OR "fentanyl-12" OR "fentanyl-25" OR "fentanyl-37" OR "fentanyl-50" OR "fentanyl-75" OR jns020qd OR leptanal OR matrifin OR pecfent OR phentanyl OR "r 4263" OR r4263 OR recuvyra OR subsys OR tanyl) #6 TS=(morphine OR anpec OR duromorph OR epimorph OR miro OR morfin OR morfina OR morphia OR morphin OR "morphine alkaloid" OR "morphine chlorhydrate" OR "morphine chloride" OR "morphine hydrochloride" OR "morphine suspension" OR morphinium OR morphium OR opso OR skenan OR "trans morphine") #7 TS=(codeine OR codein OR codipertussin OR codyl OR "methyl morphine" OR methylmorphine OR "morphine 3 methyl ether" OR "morphine monomethyl ether" OR "trans codeine") #8 TS=(methadone OR adanon OR algolysin OR algovetin OR amidon OR amidone OR "an 148" OR an148 OR anadon OR butalgin OR deamin OR depridol OR diaminon OR dolamid OR dolmed OR dolophin OR dolophine OR dorex OR eptadone OR fenadon OR heptadon OR heptadone OR heptanon OR ketalgin OR "l-polamidon" OR mecodin OR metadol OR metadon OR methaddict OR methadon OR "methadone base" OR "methadone hydrochloride" OR methadose OR miadone OR phenadon OR physeptone OR polamidon OR polamivet OR "sedo-rapide" OR symoron OR win) #9 TS=(buprenorphine OR addnok OR astec OR belbuca OR brixadi OR buprenex OR buprenorfin OR buprenorfina OR buprenorfine OR buprenorphin OR "buprenorphine hydrochloride" OR butec OR butrans OR buvidal OR cam2038 OR lepetan OR "lyn 013" OR lyn013 OR

norphin OR norspan OR probuphenine OR probuphine OR "rbp 6000" OR rbp6000 OR sixmo OR sublocade OR subutex OR temgesic OR transtec)

#10 TS=(tramadol OR ad2112 OR adamon OR adolonta OR amanda OR analab OR andalpha OR bio301 OR calmol OR "cg 315" OR "cg 315e" OR cg315 OR contramal OR conzip OR dolzam OR "e 382" OR e381 OR e382 OR marol OR monocrioxo OR noax OR nobligan OR "ns 24" OR ns24 OR prontalgin OR qdolo OR ralivia OR ryzolt OR "t-long" OR tioner OR tiparol OR topalgic OR "topalgic lp" OR toram OR tradolan OR tradonal OR tralgit OR "tramadol hcl" OR "tramadol hydrochloride" OR "tramadol lp" OR "tramadol retard" OR "tramadol sr" OR tramadolis OR tramadolo OR tramador OR tramal OR tramazac OR tramol OR tramundin OR tridol OR tridural OR trodon OR ultram OR "ultram er" OR zamadol OR zertane OR zydol OR "zydol sr" OR zytram)

#11 TS=(hydromorphone OR dihydromorphinone OR dihydromorphone OR dilaudid OR dimorphone OR exalgo OR "hydromorph contin" OR hydromorphon OR "hydromorphone hydrochloride" OR jurnista OR novolaudon OR palladon OR palladone)

#12 TS=(oxymorphone OR hydroxydihydromorphinone OR numorphan OR opana OR "opana er" OR "oxymorphone hydrochloride")

#13 TS=(cannabinoid* OR cannabis OR "cannabis sativa extract" OR "cannabis sativa resin" OR bhang OR "cannabis constituent" OR "cannabis extract" OR "cannabis leaf" OR cannador OR charas OR ganja OR hashish OR "hashish oil" OR "hemp extract" OR marihuana OR marijuana OR "medical cannabis" OR "medical marihuana" OR "medical marijuana" OR "medicinal cannabis" OR "medicinal marijuana" OR "marijuana treatment" OR dronabinol OR "1 trans delta 9 tetrahydrocannabinol" OR "delta 1 tetrahydrocannabinol" OR "delta 1 trans tetrahydrocannabinol" OR "delta 9 tetrahydrocannabinol" OR "delta 9 trans tetrahydrocannabinol" OR "delta1 tetrahydrocannabinol" OR "delta1 thc" OR "delta1 trans tetrahydrocannabinol" OR "delta9 tetrahydro cannabinol" OR "delta9 tetrahydrocannabinol" OR "delta9 trans tetrahydrocannabinol" OR "l delta 9 trans tetrahydrocannabinol" OR marinol OR "qcd 84924" OR syndros OR "tetrahydrocannabinol delta9" OR "trans delta 9 tetrahydrocannabinol" OR thc OR "delta 3 tetrahydrocannabinol" OR "delta tetrahydrocannabinol" OR "delta3 tetrahydrocannabinol" OR "sp 104" OR "tetrahydro cannabinol" OR tetrahydrocannabinal OR tetrahydrocannabinol OR tetrahydrocannabiol OR "trans tetrahydrocannabinol" OR scb)

#14 TS=(alcohol OR ethanol OR ethylalcohol)

#15 TS=("alcoholic beverage*" OR "alcoholic drink*" OR "liquor alcohol" OR absinthe OR beer OR brandy OR gin OR makgeolli OR makkoli OR makoli OR "honey wine" OR pulque OR rum OR "rice wine" OR sake OR vodka OR bourbon OR "bourbon whiskey" OR "scotch whiskey" OR whiskey OR whisky OR wine OR "apple cider" OR "apple wine" OR cider)

#16 TS=(benzodiazepine*)

#17 TS=(barbiturate* OR "barbiturate derivative*" OR "barbituric acid derivative*")

#18 TS=(ghba OR "gamma hydroxy butyric acid" OR "gamma hydroxybutyrate" OR "gamma hydroxybutyric acid")

#19 TS=(hallucinogen* OR hallucinogenic OR "hallucinogenic agent" OR "hallucinogenic drug*" OR psychedelia OR psychedelic* OR "psychedelic agent*" OR "psychedelic drug*" OR psychodelic* OR psychodysleptic OR "psychodysleptic drug" OR psychomimetic OR "psychomimetic drug" OR "psychotic drug" OR psychotomimetic OR "psychotomimetic agent" OR "psychotomimetic drug*")

#20 TS=(lsd OR delysid OR "l s d" OR "lsd 25" OR "lysergic acid diethylamide" OR lysergide)

#21 TS=(mdma OR ecstasy OR methylenedioxymethamphetamine OR midomafetamine)

#22 TS=("angel dust" OR "ci 395" OR ci395 OR "cl 395" OR "gp 121" OR phencyclidin OR phencyclidine OR "phencyclidine hydrochloride" OR phenylcyclidine OR phenylcyclidine OR sernyl OR sernylan)

#23 TS=(psilocybin OR comp360 OR "cy 39" OR indocybin OR psilocybine)

#24 TS=(mescaline OR mescalín OR "mescaline hydrochloride" OR mezcaine OR peyote OR peyotine OR peyotl)

#25 TS=(ketamine OR calipsol OR calypsol OR "ci 581" OR ci581 OR imalgene OR kalipsol OR katamine OR ketaject OR ketalar OR "ketamine hcl" OR "ketamine hydrochloride" OR ketanest OR ketased OR ketaset OR ketavet OR ketolar OR narkamon OR "sls 002" OR sls002 OR tekam OR velonarcon OR vetalar)

#26 TS=("dimethyl tryptamine" OR dimethyltryptamine OR "n dimethyltryptamine" OR "n n dimethyltryptamine")

#27 TS=(analeptic* OR "analeptic agent*" OR "analeptic drug*" OR "psychoanaleptic agent" OR stimulant* OR "stimulating agent*" OR "stimulative agent*")

#28 TS=(cocaine OR "crack cocaine" OR "beta cocaine" OR cocain OR "cocain hydrochloride" OR "cocaine hydrochloride" OR "cocaine methiodide" OR "ecgonine methyl ester benzoate" OR "l cocaine" OR neurocaine)

#29 TS=(methamphetamine OR adipex OR ambar OR corvitin OR deoxyephedrine OR desamine OR desoxyephedrine OR "desoxyephedrine hydrochloride" OR desoxyn OR desyphed OR detrex OR "dl methamphetamine" OR doe OR gerovit OR hiropon OR isophen OR "l methamphetamine" OR metamfetamine OR metamphetamine OR methamine OR methamphetamine OR "methamphetamine hcl" OR "methamphetamine hydrochloride" OR methedrine OR methoxyn OR "methyl amphetamine" OR methylamphetamine OR "methylamphetamine hydrochloride" OR "n methylamphetamine" OR norodin OR pervitin OR philopon)

#30 TS=(amphetamine OR actedron OR adipan OR adzenys OR "adzenys er" OR aktedrin OR aktedron OR alentol OR allodene OR "alpha amphetamine" OR "alpha methylphenethylamine" OR "alpha methylphenylethylamine" OR amfetamine OR amphamed OR amphamine OR amphetaine OR amphetamin OR "amphetamine detection" OR "amphetamine hydrochloride" OR "amphetamine intoxication" OR "amphetamine metabolism" OR "amphetamine resin complex" OR "amphetamine sulfate" OR "amphetamine sulphate" OR "amphetamine toxicity" OR amphetamine OR amphezamin OR anara OR "ar 19" OR ar19 OR astedin OR benzafinyl OR benzebar OR benzedrine OR benzolone OR benzpropamine OR "beta aminopropylbenzene" OR "beta phenyl isopropylamine" OR "beta phenylisopropylamine" OR betafen OR bluzedrin OR centramina OR centramine OR "d l amphetamine" OR "delta amphetamine" OR diethamine OR dipan OR elastonin OR elastonon OR euphobine OR euphodyne OR euphodyn OR evekeo OR "evekeo odt" OR fabedrine OR fenara OR fenedrin OR ibiozedrine OR isoamin OR isoamine OR isoamyne OR isomyn OR "l amphetamine" OR levamfetamine OR "levo amphetamine" OR levoamphetamine OR linampheta OR mecodrin OR mimetina OR monophos OR noclon OR norephedrane OR norphedrane OR novydrine OR "nt 0201" OR obetrol OR oktedrin OR oraldrina OR ortedrine OR percomon OR pharmamedrine OR pharmedrine OR phenamin OR phenedrine OR phenpromin OR "phenyl isopropylamine" OR phenylaminopropane OR profamina OR profetamine OR propisamine OR psychedrin OR psychedrine OR psychoton OR racephen OR raphetamine OR rhinalator OR sedolin OR simpamina OR simpamine OR simpatedrin OR sympametín OR sympamine OR sympatedrine OR theptine OR vapedrine OR zedrine)

#31 TS=("substance related disorder*" OR alcoholism OR "binge drinking" OR "alcohol drinking in college" OR "driving under the influence" OR "drug misuse" OR "prescription drug misuse" OR "inhalant abuse" OR "substance usage" OR "substance use" OR addict OR "addiction drug" OR "dependence drug" OR "drug addict" OR "drug addiction" OR "drug dependence" OR "drug dependency" OR "drug facilitation" OR "drug

habituation" OR "physical dependence" OR "substance addiction" OR "substance dependence" OR "substance dependency" OR "substance use disorder*" OR "substance-related disorder" OR toxicomania* OR toxicomanie OR "abuse drug" OR "drug abuse" OR "drug abuser" OR "drug problem" OR "abuse alcohol" OR "alcohol abuse" OR "ethanol abuse" OR "heavy episodic drinking" OR "college alcohol use" OR "college drinking" OR "college student drinking" OR "student drinking" OR "university student drinking" OR "driving drunken" OR "drunk driving" OR "drunken driver" OR "drunken driving" OR "excessive drinking" OR "hazardous drinking" OR "heavy drinking" OR "problem drinking" OR "problematic drinking" OR "addiction alcohol" OR "alcohol addiction" OR "alcohol dependence" OR "alcohol dependency" OR "alcohol dependents" OR "alcohol polyneuropathy" OR "alcohol use disorder" OR "alcohol-dependent individual" OR "alcohol-induced disorders" OR "alcohol-related disorders" OR alcoholic OR "alcoholic individual" OR "alcoholic neuropathy" OR "alcoholic polyneuritis" OR "alcoholic polyneuropathy" OR alcoholics OR "chronic alcoholism" OR "dependence alcohol" OR dipsomania* OR "ethanol dependence" OR "medicine misuse" OR nmupd OR "medication misuse" OR "non-medical use of prescription drugs" OR "nonmedical use of prescription drugs" OR "prescription medication misuse" OR "prescription medicine misuse" OR "glue sniffing" OR "sniffing glue")

#32 TS=(narcotic* OR "narcotic agent*" OR "narcotic drug*" OR "narcotic plant" OR stupefacient)

#33 TS=(addiction* OR "addictive behavior*" OR addictive OR addict* OR "addictive behaviour*" OR "addictive disorder*" OR "behavior addictive" OR "behaviour addictive" OR "chemical dependence")

#34 TS=("illegal drug*" OR "illicit drug*")

#35 TS=("multi-drug abuse" OR "multi-drug addiction" OR "multidrug abuse" OR "multiple addiction" OR "multiple drug abuse" OR "multiple drug addiction" OR "poly-drug abuse" OR "poly-drug addiction" OR "poly-drug use" OR "polydrug abuse" OR "polydrug addiction" OR "polydrug use")

#36 TS=("inhalant abuse" OR "inhalation abuse" OR "inhalation drug abuse" OR "inhalational abuse" OR "inhalational drug abuse")

#37 TS=("designer drug*" OR "controlled drug*" OR "controlled medicine*" OR "controlled substance*" OR "tobacco product*" OR "tobacco use" OR tobacco OR nicotine OR "beta pyridyl alpha n methylpyrrolidine" OR habitrol OR nicabate OR nicoderm OR "nicoderm cq" OR nicolan OR nicopatch OR nicotin OR "nicotine tts" OR nicotinell OR "nicotinell lozenge" OR "nicotinell tts" OR nicotrol OR "nicotrol inhaler" OR "nicotrol ns" OR niquitin OR "niquitin cq" OR prostep OR "x 22" OR x22)

#38 TS=("designer drug*" OR "controlled drug*" OR "controlled medicine*" OR "controlled substance*" OR tobacco OR nicotine OR "beta pyridyl alpha n methylpyrrolidine" OR habitrol OR nicabate OR nicoderm OR "nicoderm cq" OR nicolan OR nicopatch OR nicotin OR "nicotine tts" OR nicotinell OR "nicotinell lozenge" OR "nicotinell tts" OR nicotrol OR "nicotrol inhaler" OR "nicotrol ns" OR niquitin OR "niquitin cq" OR prostep OR "x 22" OR x22 OR smoking OR "behavior smoking" OR "behaviour smoking" OR "reverse smoking" OR smoker* OR "smoking behavior" OR "smoking behaviour" OR "tobacco smoking" OR "cigarette smoking" OR vaping OR cigarette* OR "filter cigarette" OR "e cigarette*" OR "electronic cigarette*" OR "electronic nicotine delivery system*" OR "e-cigarette smoking" OR "electronic cigarette smoking" OR vape* OR cigar* OR "waterpipe" OR "water pipe smoking" OR arghile OR goza OR hookah OR narghile OR shisha OR "smoking water pipe*")

#39 TS=("nitrous oxide" OR "dinitrogen monoxide" OR "dinitrogen oxide" OR "factitious air" OR "hyponitrous acid anhydride" OR lachgas OR "laughing gas" OR "nitrogen hypoxide" OR "nitrogen protoxide" OR whippet* OR nangs OR "buzz bomb*" OR "hippy crack")

#40 #1 OR #2 OR #3 OR #4 OR #5 OR #6 OR #7 OR #8 OR #9 OR #10 OR #11 OR #12 OR #13 OR #14 OR #15 OR #16 OR #17 OR #18 OR #19 OR #20 OR #21 OR #22 OR #23 OR #24 OR #25 OR #26 OR #27 OR #28 OR #29 OR #30 OR #31 OR #32 OR #33 OR #34 OR #35 OR #36 OR #37 OR #38 OR #39

#41 TS=("text analytic*" OR "text information extraction" OR "named entity extraction" OR "named entity recognition" OR "co-reference resolution" OR "relation extraction" OR "sentiment analysis" OR "emotion ai" OR "opinion mining" OR "topic modeling" OR "word embedding")

#42 TS=("language model*" OR "large language model*" OR "generative pre-trained transformer" OR "generative pre-training transformer" OR "generative pretrained transformer" OR "transformer model*" OR "bidirectional encoder representations from transformer*" OR "few shot learning" OR "zero shot learning" OR "prompt engineering" OR "text classification*" OR "word processing" OR "text processing" OR "syntactic parsing" OR "semantic analysis" OR "semantic analytic*" OR "discourse analysis" OR "text summarization")

#43 TS=("neural network*" OR "mlp multilayer perceptron" OR "mlp neural network" OR "multi-layer perceptron" OR "multilayer perceptron" OR "multilayer perceptron network" OR "multilayer perceptron neural network" OR "multiple layer perceptron" OR "cnn convolutional neural network*" OR "cnns convolutional neural networks" OR convnet OR "convoluted neural network" OR "convolution neural network" OR "convolutional anns" OR "convolutional nn" OR "convolutional artificial neural network" OR "convolutional deep neural network" OR "convolutional neural network" OR "deep convolutional neural network" OR "recursive neural network" OR "rnn recurrent neural network*" OR "rnns recurrent neural networks" OR "recurrent ann" OR "recurrent nn*" OR "recurrent artificial neural network" OR "recurrent neural network" OR "lstm model" OR "lstm network" OR "lstm neural network" OR "lstm recurrent neural network" OR "lstm-rnn*" OR "rnn-lstm" OR "long short term memory lstm network" OR "long short term memory lstm neural network" OR "long short term memory neural network" OR "long short term memory network" OR "long short-term memory recurrent neural network" OR "sequence to sequence model*" OR "shallow neural network*" OR "ann artificial neural network" OR "ann analysis" OR "ann approach" OR "ann method*" OR "ann model*" OR "ann output" OR "ann technique*" OR "ann training" OR "anns artificial neural networks" OR "artificial nn*" OR "artificial neural network*" OR "computational neural network" OR "computer neural network*" OR "connectionist model" OR "connectionist network" OR "connectionist neural network" OR "connectionist system" OR "mathematical neural network" OR "neural network computer" OR "neural network algorithm" OR "neural network model" OR "neural networks computer" OR "clinical note*" OR "free text*")

#44 TS=("natural language processing" OR "text mining" OR "text mine*")

#45 #41 OR #42 OR #43 OR #44

#46 TS=("electronic health record*" OR "ehr electronic health record" OR "electronic healthcare database" OR "electronic medical record" OR "telemedicine" OR "e-health" OR ehealth OR "tele-health" OR telehealth OR "tele medicine" OR "virtual medicine" OR "m health" OR "e visit*")

#47 #40 AND #45 AND #46

Refined by: LANGUAGES: (ENGLISH)

SCOPUS

(TITLE-ABS-KEY (opiate* OR opioid* OR allopam OR biopon OR laudanum OR nepenthe OR omnopon OR opial OR "opiate alkaloid*" OR "opium alkaloid*" OR opium OR "opium derivative*" OR "opium poppy" OR "opium tincture" OR opom OR pantopon OR papaveretum OR pavon OR tetrapon)) OR (TITLE-ABS-KEY (heroin OR acetomorphine OR "diacetyl morphine" OR diacetylmorphine OR "diacetylmorphine hydrochloride" OR diamorphine OR "diamorphine hydrochloride" OR diaphorin OR "heroin hydrochloride" OR heroine OR morphacetin)) OR (TITLE-ABS-KEY (oxycodone OR alivio OR bionone OR "col 003" OR col003 OR dihydrohydroxycodone OR dihydron OR endone OR eubine OR eucodal OR eucodalum OR eukodal OR nargenol OR "nsc 19043" OR opton OR ossicodone OR oxanest OR oxaydo OR oxecta OR oxiconona OR oxicone OR "oxy ir" OR oxycodon OR "oxycodone hcl" OR "oxycodone hydrochloride" OR oxycone OR oxycontin OR "oxycontin neo" OR oxydol OR oxyfast OR oxygesic OR oxyir OR oxylan OR oxyneo OR oxynorm OR oxypro OR pavinal OR pronarcin OR "pti 821" OR pti821 OR remoxy OR roxicodone OR roxybond OR xtampza OR "xtampza er")) OR (TITLE-ABS-KEY (hydrocodone OR bekadid OR dico OR dicodid OR

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"psychedelic agent*" OR "psychedelic drug*" OR psychodelic* OR psychodysleptic OR "psychodysleptic drug" OR psychomimetic OR "psychomimetic drug" OR "psychotic drug" OR psychotomimetic OR "psychotomimetic agent" OR "psychotomimetic drug*")) OR (TITLE-ABS-KEY (lsd OR delysid OR "l s d" OR "lsd 25" OR

"lysergic acid diethylamide" OR lysergide)) OR (TITLE-ABS-KEY (mdma OR ecstasy OR methylenedioxymethamphetamine OR midomafetamine)) OR (TITLE-ABS-KEY ("angel dust" OR "ci 395" OR ci395 OR "cl 395" OR "gp 121" OR phencyclidin OR phencyclidine OR "phencyclidine hydrochloride" OR phenycyclidine OR phenylcyclidine OR sernyl OR sernylan)) OR (TITLE-ABS-KEY (psilocybin OR comp360 OR "cy 39" OR indocybin OR psilocybine)) OR (TITLE-ABS-KEY (mescaline OR mescalol OR "mescaline hydrochloride" OR mezcaline OR peyote OR peyotine OR peyotl)) OR (TITLE-ABS-KEY (ketamine OR calipso OR calypso OR "ci 581" OR ci581 OR imalgene OR kalipso OR katamine OR ketajet OR ketalar OR "ketamine hcl" OR "ketamine hydrochloride" OR ketanest OR ketased OR ketaset OR ketavet OR ketolar OR narkamon OR "sls 002" OR sls002 OR tekam OR velonarcon OR vetalar)) OR (TITLE-ABS-KEY ("dimethyl tryptamine" OR dimethyltryptamine OR "n dimethyltryptamine" OR "n n dimethyltryptamine")) OR (TITLE-ABS-KEY (analeptic* OR "analeptic agent*" OR "analeptic drug*" OR "psychoanaleptic agent" OR stimulant* OR "stimulating agent*" OR "stimulative agent*")) OR (TITLE-ABS-KEY (cocaine OR "crack cocaine" OR "beta cocaine" OR cocain OR "cocain hydrochloride" OR "cocaine hydrochloride" OR "cocaine methiodide" OR "ecgonine methyl ester benzoate" OR "l cocaine" OR neurocaine)) OR (TITLE-ABS-KEY (methamphetamine OR adipex OR ambar OR corvitin OR deoxyephedrine OR desamine OR desoxyephedrine OR "desoxyephedrine hydrochloride" OR desoxyn OR desyphed OR detrex OR "dl methamphetamine" OR doe OR gerovit OR hiropon OR isophen OR "l methamphetamine" OR metamfetamine OR metamphetamine OR methamine OR methamphetamin OR "methamphetamine hcl" OR "methamphetamine hydrochloride" OR methedrine OR methoxyn OR "methyl amphetamine" OR methylamphetamine OR "methylamphetamine hydrochloride" OR "n methylamphetamine" OR norodin OR pervitin OR philopon)) OR (TITLE-ABS-KEY (amphetamine OR actedron OR adipan OR adzenys OR "adzenys er" OR aktedrin OR aktedron OR alentol OR allodene OR "alpha amphetamine" OR "alpha methylphenethylamine" OR "alpha methylphenylethylamine" OR amfetamine OR amphamed OR amphamine OR amphetaime OR amphetamin OR "amphetamine detection" OR "amphetamine hydrochloride" OR "amphetamine intoxication" OR "amphetamine metabolism" OR "amphetamine resin complex" OR "amphetamine sulfate" OR "amphetamine sulphate" OR "amphetamine toxicity" OR amphethamine OR amphezamin OR anara OR "ar 19" OR ar19 OR astedin OR benzafinyl OR benzebar OR benzedrine OR benzolone OR benzpropamine OR "beta aminopropylbenzene" OR "beta phenyl isopropylamine" OR "beta phenylisopropylamine" OR betafen OR bluzedrin OR centramina OR centramine OR "d l amphetamine" OR "delta amphetamine" OR diethamine OR dipan OR elastonin OR elastonon OR euphobine OR euphodie OR euphodyn OR evekeo OR "evekeo odt" OR fabedrine OR fenara OR fenedrin OR ibiozedrine OR isoamin OR isoamine OR isoamyne OR isomyn OR "l amphetamine" OR levamfetamine OR "levo amphetamine" OR levoamphetamine OR linampheta OR mecodrin OR mimetina OR monophos OR noclon OR norephedrine OR norphedrine OR novydrine OR "nt 0201" OR obetrol OR oktedrin OR oraldrina OR ortedrine OR percomon OR pharmamedrine OR pharmedrine OR phenamin OR phenedrine OR phenpromin OR "phenyl isopropylamine" OR phenylaminopropane OR profamina OR profetamine OR propisamine OR psychedrin OR psychedrine OR psychoton OR racephen OR raphetamine OR rhinalator OR sedolin OR simpamina OR simpamine OR simpatedrin OR sympametin OR sympamine OR sympatedrine OR theptine OR vapedrine OR zedrine)) OR (TITLE-ABS-KEY ("substance related disorder*" OR alcoholism OR "binge drinking" OR "alcohol drinking in college" OR "driving under the influence" OR "drug misuse" OR "prescription drug misuse" OR "inhalant abuse" OR "substance usage" OR "substance use" OR addict OR "addiction drug" OR "dependence drug" OR "drug addict" OR "drug addiction" OR "drug dependence" OR "drug dependency" OR "drug facilitation" OR "drug habituation" OR "physical dependence" OR "substance addiction" OR "substance dependence" OR "substance dependency" OR "substance use disorder*" OR "substance-related disorder" OR toxicomania* OR toxicomanie OR "abuse drug" OR "drug abuse" OR "drug abuser" OR "drug problem" OR "abuse alcohol" OR "alcohol abuse" OR "ethanol abuse" OR "heavy episodic drinking" OR "college alcohol use" OR "college drinking" OR "college student drinking" OR "student drinking" OR "university student drinking" OR "driving drunken" OR "drunk driving" OR "drunken driver" OR "drunken driving" OR "excessive drinking" OR "hazardous drinking" OR "heavy drinking" OR "problem drinking" OR "problematic drinking" OR "addiction alcohol" OR "alcohol addiction" OR "alcohol dependence" OR "alcohol dependency" OR "alcohol dependents" OR "alcohol polyneuropathy" OR "alcohol use disorder" OR "alcohol-dependent individual" OR "alcohol-induced disorders" OR "alcohol-related disorders" OR alcoholic OR "alcoholic individual" OR "alcoholic neuropathy" OR "alcoholic polyneuritis" OR "alcoholic polyneuropathy" OR alcoholics OR "chronic alcoholism" OR "dependence alcohol" OR dipsomania* OR "ethanol dependence" OR "medicine misuse" OR nmupd OR "medication misuse" OR "non-medical use of prescription drugs" OR "nonmedical use of prescription

drugs" OR "prescription medication misuse" OR "prescription medicine misuse" OR "glue sniffing" OR "sniffing glue")) OR (TITLE-ABS-KEY (narcotic* OR "narcotic agent*" OR "narcotic drug*" OR "narcotic plant" OR stupefacient)) OR (TITLE-ABS-KEY (addiction* OR "addictive behavior*" OR addictive OR addict* OR "addictive behaviour*" OR "addictive disorder*" OR "behavior addictive" OR "behaviour addictive" OR "chemical dependence")) OR (TITLE-ABS-KEY ("illegal drug*" OR "illicit drug*")) OR (TITLE-ABS-KEY ("multi-drug abuse" OR "multi-drug addiction" OR "multidrug abuse" OR "multiple addiction" OR "multiple drug abuse" OR "multiple drug addiction" OR "poly-drug abuse" OR "poly-drug addiction" OR "poly-drug use" OR "polydrug abuse" OR "polydrug addiction" OR "polydrug use")) OR (TITLE-ABS-KEY ("inhalant abuse" OR "inhalation abuse" OR "inhalation drug abuse" OR "inhalational abuse" OR "inhalational drug abuse")) OR (TITLE-ABS-KEY ("designer drug*" OR "controlled drug*" OR "controlled medicine*" OR "controlled substance*" OR "tobacco product*" OR "tobacco use" OR tobacco OR nicotine OR "beta pyridyl alpha n methylpyrrolidine" OR habitrol OR nicabate OR nicoderm OR "nicoderm cq" OR nicolan OR nicopatch OR nicotin OR "nicotine tts" OR "nicotinell" OR "nicotinell lozenge" OR "nicotinell tts" OR nicotrol OR "nicotrol inhaler" OR "nicotrol ns" OR niquitin OR "niquitin cq" OR prostep OR "x 22" OR x22)) OR (TITLE-ABS-KEY ("designer drug*" OR "controlled drug*" OR "controlled medicine*" OR "controlled substance*" OR tobacco OR nicotine OR "beta pyridyl alpha n methylpyrrolidine" OR habitrol OR nicabate OR nicoderm OR "nicoderm cq" OR nicolan OR nicopatch OR nicotin OR "nicotine tts" OR "nicotinell" OR "nicotinell lozenge" OR "nicotinell tts" OR nicotrol OR "nicotrol inhaler" OR "nicotrol ns" OR niquitin OR "niquitin cq" OR prostep OR "x 22" OR x22 OR smoking OR "behavior smoking" OR "behaviour smoking" OR "reverse smoking" OR smoker* OR "smoking behavior" OR "smoking behaviour" OR "tobacco smoking" OR "cigarette smoking" OR vaping OR cigarette* OR "filter cigarette" OR "e cigarette*" OR "electronic cigarette*" OR "electronic nicotine delivery system*" OR "e-cigarette smoking" OR "electronic cigarette smoking" OR vape* OR cigar* OR waterpipe OR "water pipe smoking" OR arghile OR goza OR hookah OR narghile OR shisha OR "smoking water pipe*")) OR (TITLE-ABS-KEY ("nitrous oxide" OR "dinitrogen monoxide" OR "dinitrogen oxide" OR "factitious air" OR "hyponitrous acid anhydride" OR lachgas OR "laughing gas" OR "nitrogen hypoxide" OR "nitrogen protoxide" OR whippet* OR nangs OR "buzz bomb*" OR "hippy crack"))

AND

(TITLE-ABS-KEY ("text analytic*" OR "text information extraction" OR "named entity extraction" OR "named entity recognition" OR "co-reference resolution" OR "relation extraction" OR "sentiment analysis" OR "emotion ai" OR "opinion mining" OR "topic modeling" OR "word embedding")) OR (TITLE-ABS-KEY ("language model*" OR "large language model*" OR "generative pre-trained transformer" OR "generative pre-training transformer" OR "generative pretrained transformer" OR "transformer model*" OR "bidirectional encoder representations from transformer*" OR "few shot learning" OR "zero shot learning" OR "prompt engineering" OR "text classification*" OR "word processing" OR "text processing" OR "syntactic parsing" OR "semantic analysis" OR "semantic analytic*" OR "discourse analysis" OR "text summarization")) OR (TITLE-ABS-KEY ("neural network*" OR "mlp multilayer perceptron" OR "mlp neural network" OR "multi-layer perceptron" OR "multilayer perceptron" OR "multilayer perceptron network" OR "multilayer perceptron neural network" OR "multiple layer perceptron" OR "cnn convolutional neural network*" OR "cnns convolutional neural networks" OR convnet OR "convoluted neural network" OR "convolution neural network" OR "convolutional anns" OR "convolutional nn" OR "convolutional artificial neural network" OR "convolutional deep neural network" OR "convolutional neural network" OR "deep convolutional neural network" OR "recursive neural network" OR "rnn recurrent neural network*" OR "rnns recurrent neural networks" OR "recurrent ann" OR "recurrent nn*" OR "recurrent artificial neural network" OR "recurrent neural network" OR "lstm model" OR "lstm network" OR "lstm neural network" OR "lstm recurrent neural network" OR "lstm-rnn*" OR "rnn-lstm" OR "long short term memory lstm network" OR "long short term memory lstm neural network" OR "long short term memory neural network" OR "long short term memory network" OR "long short-term memory recurrent neural network" OR "sequence to sequence model*" OR "shallow neural network*" OR "ann artificial neural network" OR "ann analysis" OR "ann approach" OR "ann method*" OR "ann model*" OR "ann output" OR "ann technique*" OR "ann training" OR "anns artificial neural networks" OR "artificial nn*" OR "artificial neural network*" OR "computational neural network" OR "computer neural network*" OR "connectionist model" OR "connectionist network" OR "connectionist neural network" OR "connectionist system" OR "mathematical neural network" OR "neural network computer" OR "neural network algorithm" OR "neural network model" OR "neural

	networks computer" OR "clinical note*" OR "free text*")) OR (TITLE-ABS-KEY ("natural language processing" OR "text mining" OR "text mine*")) AND (TITLE-ABS-KEY ("electronic health record*" OR "ehr electronic health record" OR "electronic healthcare database" OR "electronic medical record" OR telemedicine OR "e-health" OR ehealth OR "tele-health" OR telehealth OR "tele medicine" OR "virtual medicine" OR "m health" OR "e visit*")) AND (LIMIT-TO (LANGUAGE , "English"))
ACM DIGITAL LIBRARY	[[AllField:(opioid OR opiate OR heroin OR "diacetylmorphine" OR "diamorphine" OR oxycodone OR "oxycontin" OR hydrocodone OR fentanyl OR "duragesic" OR morphine OR codeine OR methadone OR "dolophine" OR buprenorphine OR "subutex" OR tramadol OR "ultram" OR hydromorphone OR "dilaudid" OR oxymorphone OR cannabinoid OR cannabis OR marijuana OR "medical marijuana" OR THC OR "tetrahydrocannabinol" OR dronabinol OR alcohol OR ethanol OR "alcoholic beverage" OR beer OR wine OR benzodiazepine OR barbiturate OR "gamma hydroxybutyrate" OR "gamma hydroxybutyric acid" OR GHB OR hallucinogen OR psychedelic OR LSD OR "lysergic acid diethylamide" OR MDMA OR ecstasy OR "methylenedioxymethamphetamine" OR phencyclidine OR PCP OR psilocybin OR mescaline OR peyote OR ketamine OR "dimethyltryptamine" OR DMT OR stimulant OR cocaine OR "crack cocaine" OR methamphetamine OR amphetamine OR "substance abuse" OR "drug abuse" OR "substance dependence" OR "drug dependence" OR "substance use disorder" OR addiction OR alcoholism OR "binge drinking" OR "drug misuse" OR "prescription drug misuse" OR narcotic OR "illicit drug" OR "illegal drug" OR "designer drug" OR "controlled substance" OR tobacco OR nicotine OR smoking OR cigarette OR vaping OR "e-cigarette" OR "electronic cigarette" OR "nitrous oxide" OR "laughing gas")]] AND [[AllField:("natural language processing" OR NLP OR "text mining" OR "text analytic*" OR "text information extraction" OR "named entity recognition" OR NER OR "named entity extraction" OR "relation extraction" OR "sentiment analysis" OR "opinion mining" OR "topic modeling" OR "word embedding" OR "language model" OR "large language model" OR LLM OR "transformer" OR GPT OR BERT OR "generative pre-trained transformer" OR "bidirectional encoder representations" OR "few shot learning" OR "zero shot learning" OR "prompt engineering" OR "text classification" OR "text processing" OR "word processing" OR "syntactic parsing" OR "semantic analysis" OR "discourse analysis" OR "text summarization" OR "neural network" OR "artificial neural network" OR ANN OR "deep learning" OR "machine learning" OR CNN OR "convolutional neural network" OR RNN OR "recurrent neural network" OR LSTM OR "long short-term memory" OR "multilayer perceptron" OR MLP OR "connectionist model" OR "clinical note" OR "free text")]] AND [[AllField:("electronic health record" OR EHR OR "electronic medical record" OR EMR OR "electronic healthcare record" OR "electronic health database" OR "health information system" OR "clinical information system" OR telemedicine OR "e-health" OR ehealth OR telehealth OR "tele-health" OR "virtual medicine" OR "mobile health" OR "m-health" OR mhealth OR "e-visit")]]
IEEE XPLORE	(("All Metadata":opioid) OR ("All Metadata":opiate) OR ("All Metadata":heroin) OR ("All Metadata":diacetylmorphine) OR ("All Metadata":diamorphine) OR ("All Metadata":oxycodone) OR ("All Metadata":oxycontin) OR ("All Metadata":hydrocodone) OR ("All Metadata":fentanyl) OR ("All Metadata":duragesic) OR ("All Metadata":morphine) OR ("All Metadata":codeine) OR ("All Metadata":methadone) OR ("All Metadata":dolophine) OR ("All Metadata":buprenorphine) OR ("All Metadata":subutex) OR ("All Metadata":tramadol) OR ("All Metadata":ultram) OR ("All Metadata":hydromorphone) OR ("All Metadata":dilaudid) OR ("All Metadata":oxymorphone) OR ("All Metadata":cannabinoid) OR ("All Metadata":cannabis) OR ("All Metadata":marijuana) OR ("All Metadata": "medical marijuana") OR ("All

Metadata":THC) OR ("All Metadata":tetrahydrocannabinol) OR ("All Metadata":dronabinol) OR ("All Metadata":alcohol) OR ("All Metadata":ethanol) OR ("All Metadata":alcoholic beverage") OR ("All Metadata":beer) OR ("All Metadata":wine) OR ("All Metadata":benzodiazepine) OR ("All Metadata":barbiturate) OR ("All Metadata":gamma hydroxybutyrate") OR ("All Metadata":gamma hydroxybutyric acid") OR ("All Metadata":GHB) OR ("All Metadata":hallucinogen) OR ("All Metadata":psychedelic) OR ("All Metadata":LSD) OR ("All Metadata":lysergic acid diethylamide") OR ("All Metadata":MDMA) OR ("All Metadata":ecstasy) OR ("All Metadata":methylenedioxymethamphetamine) OR ("All Metadata":phencyclidine) OR ("All Metadata":PCP) OR ("All Metadata":psilocybin) OR ("All Metadata":mescaline) OR ("All Metadata":peyote) OR ("All Metadata":ketamine) OR ("All Metadata":dimethyltryptamine) OR ("All Metadata":DMT) OR ("All Metadata":stimulant) OR ("All Metadata":cocaine) OR ("All Metadata":crack cocaine") OR ("All Metadata":methamphetamine) OR ("All Metadata":amphetamine) OR ("All Metadata":substance abuse") OR ("All Metadata":drug abuse") OR ("All Metadata":substance dependence") OR ("All Metadata":drug dependence") OR ("All Metadata":substance use disorder") OR ("All Metadata":addiction) OR ("All Metadata":alcoholism) OR ("All Metadata":binge drinking") OR ("All Metadata":drug misuse") OR ("All Metadata":prescription drug misuse") OR ("All Metadata":narcotic) OR ("All Metadata":illicit drug") OR ("All Metadata":illegal drug") OR ("All Metadata":designer drug") OR ("All Metadata":controlled substance") OR ("All Metadata":tobacco) OR ("All Metadata":nicotine) OR ("All Metadata":smoking) OR ("All Metadata":cigarette) OR ("All Metadata":vaping) OR ("All Metadata":e-cigarette") OR ("All Metadata":electronic cigarette") OR ("All Metadata":nitrous oxide") OR ("All Metadata":laughing gas"))

AND

((("All Metadata":natural language processing") OR ("All Metadata":NLP) OR ("All Metadata":text mining") OR ("All Metadata":text analytics") OR ("All Metadata":text information extraction") OR ("All Metadata":named entity recognition") OR ("All Metadata":NER) OR ("All Metadata":named entity extraction") OR ("All Metadata":relation extraction") OR ("All Metadata":sentiment analysis") OR ("All Metadata":opinion mining") OR ("All Metadata":topic modeling") OR ("All Metadata":word embedding") OR ("All Metadata":language model") OR ("All Metadata":large language model") OR ("All Metadata":LLM) OR ("All Metadata":transformer) OR ("All Metadata":GPT) OR ("All Metadata":BERT) OR ("All Metadata":generative pre-trained transformer") OR ("All Metadata":bidirectional encoder representations") OR ("All Metadata":few shot learning") OR ("All Metadata":zero shot learning") OR ("All Metadata":prompt engineering") OR ("All Metadata":text classification") OR ("All Metadata":text processing") OR ("All Metadata":word processing") OR ("All Metadata":syntactic parsing") OR ("All Metadata":semantic analysis") OR ("All Metadata":discourse analysis") OR ("All Metadata":text summarization") OR ("All Metadata":neural network") OR ("All Metadata":artificial neural network") OR ("All Metadata":ANN) OR ("All Metadata":deep learning") OR ("All Metadata":machine learning") OR ("All Metadata":CNN) OR ("All Metadata":convolutional neural network") OR ("All Metadata":RNN) OR ("All Metadata":recurrent neural network") OR ("All Metadata":LSTM) OR ("All Metadata":long short-term memory") OR ("All Metadata":multilayer perceptron") OR ("All Metadata":MLP) OR ("All Metadata":connectionist model") OR ("All Metadata":clinical note") OR ("All Metadata":free text"))

AND

((("All Metadata":electronic health record") OR ("All Metadata":EHR) OR ("All Metadata":electronic medical record") OR ("All Metadata":EMR) OR ("All Metadata":electronic healthcare record") OR ("All Metadata":electronic health database") OR ("All Metadata":health information system") OR ("All Metadata":clinical information system") OR ("All Metadata":telemedicine) OR ("All Metadata":e-health") OR ("All Metadata":chealth") OR ("All Metadata":telehealth") OR ("All Metadata":tele-health") OR ("All Metadata":virtual medicine") OR ("All Metadata":mobile health") OR ("All Metadata":m-health") OR ("All Metadata":mhealth) OR ("All Metadata":e-visit"))

Table S2. Gold Standard References (N=83)

Study ID	Title	Substances covered	NLP Methodology	DOI	Authors	Year	Journal/Conference	Publisher
Yang 2020	A Natural Language Processing Tool to Extract Quantitative Smoking Status from Clinical Narratives	Tobacco	Rule-based	10.1109/ICHI48887.2020.9374369	Xi Yang; Hanyuan Yang; Tianchen Lyu; Shuang Yang; Yi Guo; Jiang Bian; Hua Xu; Yonghui Wu	2020	2020 IEEE ICHI (Conference/Proceedings)	IEEE
Bhate 2023	Zero-shot Learning with Minimum Instruction to Extract Social Determinants and Family History from Clinical Notes using GPT Model	Alcohol; Tobacco; Other: Drug	Large Language Models (LLMs) / Transformer Based Models	10.1109/BigData59044.2023.10386811	Neel Jitesh Bhate; Ansh Mittal; Zhe He; Xiao Luo	2023	2023 IEEE BigData (Conference/Proceedings)	IEEE
Alzoubi 2018	An Automated System for Identifying Alcohol Use Status from Clinical Text	Alcohol	Rule-based; Conventional Machine Learning	10.1109/iCCECO ME.2018.8658578	Hadeel Alzoubi; Naeem Ramzan; Raid Alzubi; Ehsan Mesbahi	2018	2018 IEEE iCCECE (Conference/Proceedings)	IEEE
Zeng 2006	Extracting principal diagnosis, co-morbidity and smoking status for asthma research: Evaluation of a natural language processing system	Tobacco	Rule-based; Conventional Machine Learning	10.1186/1472-6947-6-30	Qing T Zeng; Sergey Goryachev; Scott Weiss; Margarita Sordo; Shawn N Murphy; Ross Lazarus	2006	BMC Medical Informatics and Decision Making (Journal)	Springer Nature
Yu 2021	A Study of Social and Behavioral Determinants of Health in Lung Cancer Patients Using Transformers-based Natural Language Processing Models	Tobacco	Deep Learning (RNN, LSTM, GRU,); Large Language Models (LLMs) / Transformer Based Models	PMCID: PMC8861705 (PMID 35309014)	Yu Z; Yang X; Dang C; Wu S; Adekkanattu P; Pathak J; George TJ; Hogan WR; Guo Y; Bian J; Wu Y	2021	AMIA Symposium Proceedings (Conference/Proceedings)	AMIA
Wicentowski 2008	Using Implicit Information to Identify Smoking Status in Smoke-blind Medical Discharge Summaries	Tobacco	Rule-based; Conventional Machine Learning	10.1197/jamia.M2440	R. Wicentowski; M. R. Sydes	2008	JAMIA (Journal)	OUP
Wang 2018	A comparison of word embeddings for the biomedical natural language processing	Tobacco	Deep Learning (RNN, LSTM, GRU,)	10.1016/j.jbi.2018.09.008	Yanshan Wang; Sijia Liu; Naveed Afzal; Majid Rastegar-Mojarad; Liwei Wang; Feichen Shen; Paul Kingsbury; Hongfang Liu	2018	Journal of Biomedical Informatics (Journal)	Elsevier

Turchin 2023	Comparison of BERT implementations for natural language processing of narrative medical documents	Tobacco	Large Language Models (LLMs) / Transformer Based Models	10.1016/j.imu.2022.101139	Alexander Turchin; Stanislav Masharsky; Marinka Zitnik	2023	Informatics in Medicine Unlocked (Journal)	Elsevier
Soysal 2018	CLAMP - a toolkit for efficiently building customized clinical natural language processing pipelines	Tobacco	Rule-based; Conventional Machine Learning	10.1093/jamia/ocx132	Ergin Soysal; Jingqi Wang; Min Jiang; Yonghui Wu; Serguei Pakhomov; Hongfang Liu; Hua Xu	2018	JAMIA (Journal)	OUP
Shah-Mohammadi 2024	Extraction of Substance Use Information From Clinical Notes: Generative Pretrained Transformer-Based Investigation	Alcohol; Tobacco; Any Substance Not Otherwise Specified	Large Language Models (LLMs) / Transformer Based Models	10.2196/56243	Fatemeh Shah-Mohammadi; Joseph Finkelstein	2024	JMIR Medical Informatics (Journal)	JMIR
Sajdeya 2023	Developing and validating a natural language processing algorithm to extract preoperative cannabis use status documentation from unstructured narrative clinical notes	Cannabis	Conventional Machine Learning; Deep Learning (RNN, LSTM, GRU,)	10.1093/jamia/ocad080	Ruba Sajdeya; Mamoun T Mardini; Patrick J Tighe; Ronald L Ison; Chen Bai; Sebastian Jugl; Gao Hanzhi; Kimia Zandbiglari; Farzana I Adiba; Almut G Winterstein; Thomas A Pearson; Robert L Cook; Masoud Rouhizadeh	2023	JAMIA (Journal)	OUP
Roy 2024	Large-scale identification of social and behavioral determinants of health from clinical notes: comparison of Latent Semantic Indexing and Generative Pretrained Transformer (GPT) models	Alcohol; Opioids; Cocaine; Tobacco	Conventional Machine Learning; Large Language Models (LLMs) / Transformer Based Models	10.1186/s12911-024-02705-x	Sujoy Roy; Shane Morrell; Lili Zhao; Ramin Homayouni	2024	BMC Medical Informatics and Decision Making (Journal)	Springer Nature
Petit-Jean 2024	Collaborative and privacy-enhancing workflows on a clinical data warehouse: an example developing natural language processing pipelines to detect medical conditions	Alcohol; Tobacco	Rule-based; Large Language Models (LLMs) / Transformer Based Models	10.1093/jamia/ocae069	Thomas Petit-Jean; Christel Gérardin; Emmanuelle Berthelot; Gilles Chatellier; Marie Frank; Xavier Tannier; Emmanuelle Kempf; Romain Bey	2024	JAMIA (Journal)	OUP

Muizelaar 2024	Extracting patient lifestyle characteristics from Dutch clinical text with BERT models	Alcohol; Tobacco; Any Substance Not Otherwise Specified	Large Language Models (LLMs) / Transformer Based Models	10.1186/s12911-024-02557-5	Hielke Muizelaar; Marcel Haas; Koert van Dortmont; Peter van der Putten; Marco Spruit	2024	BMC Medical Informatics and Decision Making (Journal)	Springer Nature
McCormick 2008	Use of semantic features to classify patient smoking status	Other: Smoking	Rule-based	PMID: 18998969	McCormick PJ; Elhadad N; Stetson PD	2008	AMIA Symposium Proceedings (Conference/Proceedings)	AMIA
Lybarger 2018	Using Neural Multi-task Learning to Extract Substance Abuse Information from Clinical Notes	Alcohol; Benzodiazepines; Tobacco; Other: Drug	Deep Learning (RNN, LSTM, GRU,)	PMCID: PMC6371261	Lybarger K; Yetisgen M; Ostendorf M	2018	AMIA Symposium Proceedings (Conference/Proceedings)	AMIA
Lingeman 2017	Detecting Opioid-Related Aberrant Behavior using Natural Language Processing	Opioids; Cannabis; Cocaine	Conventional Machine Learning	PMCID: PMC5977697	Lingeman JM; Wang P; Becker W; Yu H	2017	AMIA Symposium Proceedings (Conference/Proceedings)	AMIA
Harris 2020	Improving the Utility of Tobacco-Related Problem List Entries Using Natural Language Processing	Tobacco	Rule-based; Conventional Machine Learning	PMCID: PMC8075422	Harris DR; Henderson DW; Corbeau A	2020	AMIA Symposium Proceedings (Conference/Proceedings)	AMIA
Goodman-Meza 2022	Natural Language Processing and Machine Learning to Identify People Who Inject Drugs in Electronic Health Records	Polysubstance use	Rule-based; Conventional Machine Learning	10.1093/ofid/ofac471	David Goodman-Meza; Amber Tang; Babak Aryanfar; Sergio Vazquez; Adam J Gordon; Michihiko Goto; Matthew Bidwell Goetz; Steven Shoptaw; Alex A T Bui	2022	Open Forum Infectious Diseases (Journal)	OUP
Gabriel 2023	Leveraging a Natural Language Processing Model (Transformers) on Electronic Medical Record Notes to Classify Persistent Opioid Use After Surgery	Opioids	Large Language Models (LLMs) / Transformer Based Models	10.1213/ANE.0000000006579	Rodney A. Gabriel; Brian H. Park; Soraya Mehdipour; Dale N. Bongbong; Sierra Simpson; Ruth S. Waterman	2023	Anesthesia & Analgesia (Journal)	Wolters Kluwer

Dligach 2019	Toward a clinical text encoder: Pretraining for clinical natural language processing with applications to substance misuse	Alcohol; Opioids	Conventional Machine Learning; Deep Learning (RNN, LSTM, GRU,)	10.1093/jamia/ocz072	Dmitriy Dligach; Majid Afshar; Timothy Miller	2019	JAMIA (Journal)	OUP
Clark 2008	Identifying Smokers with a Medical Extraction System	Tobacco	Rule-based; Conventional Machine Learning	10.1197/jamia.M2442	C. Clark; K. Good; L. Jezierny; M. Macpherson; B. Wilson; U. Chajewska	2008	JAMIA (Journal)	OUP
Wang 2020	Opioid2FHIR: A system for extracting FHIR-compatible opioid prescriptions from clinical text	Opioids	Rule-based; Deep Learning (RNN, LSTM, GRU,)	10.1109/BIBM49941.2020.9313258	Jingqi Wang; William Christopher Mathews; Huy Anh Pham; Hua Xu; Yaoyun Zhang	2020	2020 IEEE BIBM (Conference/Proceedings)	IEEE
Topaz 2019	Extracting alcohol and substance abuse status from clinical notes: The added value of nursing data	Alcohol; Any Substance Not Otherwise Specified	Conventional Machine Learning	10.3233/SHTI190386	Maxim Topaz; Ludmila Murga; Ofrit Bar-Bachar; Kenrick Cato; Sarah Collins	2019	Studies in Health Technology and Informatics (Conference/Proceedings)	IOS Press
Patel 2022	Develop a Natural Language Processing Pipeline to Automate Extraction of Periodontal Disease Information from Electronic Dental Clinical Notes	Tobacco	Rule-based	10.1145/3545729.3545744	Jay Sureshbhai Patel; Rishi Rao; Ryan Brandon; Vishnu Iyer; Jasim M. Albandar; Marisol Tellez; Joachim Krois; Huanmei Wu	2022	2022 ICMHI (Conference/Proceedings)	ACM
Roosan 2024	Artificial Intelligence-Powered Large Language Transformer Models for Opioid Abuse and Social Determinants of Health Detection for the Underserved Population	Opioids	Large Language Models (LLMs) / Transformer Based Models	10.5220/0012717200003756	Don Roosan; Yanting Wu; Jay Chok; Christopher Sanine; Tiffany Khou; Yawen Li; Hasiba Khan	2024	DATA 2024 (13th International Conference on Data Science, Technology and Applications) (Conference/Proceedings)	SciTe Press
Mowery 2017	Investigating the Documentation of Electronic Cigarette Use in the Veteran Affairs Electronic Health Record: A Pilot Study	Tobacco; Other: Electronic Cigarette	Rule-based	10.18653/v1/W17-2335	Danielle Mowery; Brett South; Olga Patterson; Shu-Hong Zhu; Mike Conway	2017	BioNLP (Conference/Proceedings)	ACL

Kwon 2024	ODD: A Benchmark Dataset for the Natural Language Processing Based Opioid Related Aberrant Behavior Detection	Opioids	Large Language Models (LLMs) / Transformer Based Models	10.18653/v1/2024.naacl-long.244	Kwon S; Wang X; Liu W; Druhl E; Sung ML; Reisman JI; Li W; Kerns RD; Becker W; Yu H	2024	2024 NAACL (Conference/Proceedings)	ACL
Kugic 2022	Alcohol Status Standardization from Clinical Real World Data with Transformer Architectures	Alcohol	Large Language Models (LLMs) / Transformer Based Models	10.1109/ICHI54592.2022.00043	Amila Kugic; Leon Magnus Potjan; Larissa Marije Hammer; Stefan Schulz; Markus Kreuzthaler	2022	2022 IEEE ICHI (Conference/Proceedings)	IEEE
Jonnagaddala 2015	A preliminary study on automatic identification of patient smoking status in unstructured electronic health records	Tobacco	Rule-based; Conventional Machine Learning	10.18653/v1/W15-3818	Jitendra Jonnagaddala; Hong-Jie Dai; Pradeep Ray; Siaw-Teng Liaw	2015	BioNLP (Conference/Proceedings)	ACL
Figuerola 2014	Identifying and extracting patient smoking status information from clinical narrative texts in Spanish	Tobacco	Conventional Machine Learning	10.1109/EMBC.2014.6944182	Rosa L. Figuerola; Diego A. Soto; Esteban J. Pino	2014	2014 IEEE EMBC (Conference/Proceedings)	IEEE
Alba 2024	Development of a Natural Language Processing System to Identify Clinical Documentation of Electronic Cigarette Use	Other: Electronic Cigarette	Rule-based; Large Language Models (LLMs) / Transformer Based Models	10.3233/SHTI231047	Patrick R. Alba; Qiwei Gan; Mengke Hu; Shu-Hong Zhu; Scott E. Sherman; Scott L. DuVall; Mike Conway	2024	Studies in Health Technology and Informatics (Conference/Proceedings)	IOS Press
Zhu 2022	Automatically identifying opioid use disorder in non-cancer patients on chronic opioid therapy	Opioids	Rule-based	10.1177/14604582221107808	Vivienne J Zhu; Leslie A Lenert; Kelly S Barth; Kit N Simpson; Hong Li; Michael Kopscik; Kathleen T Brady	2022	Health Informatics Journal (Journal)	SAGE
Yusufov 2022	Natural Language Processing for Computer-Assisted Chart Review to Assess Documentation of Substance use and Psychopathology in Heart Failure Patients Awaiting Cardiac Resynchronization Therapy	Any Substance Not Otherwise Specified	Rule-based	10.1016/j.jpainsymman.2022.06.007	Miryam Yusufov; William F. Pirl; Ilana Braun; James A. Tulskey; Charlotta Lindvall	2022	Journal of Pain and Symptom Management (Journal)	Elsevier
Wu 2013	Evaluation of Smoking Status Identification Using Electronic Health Records and Open-Text Information in a Large Mental Health Case Register	Tobacco	Rule-based	10.1371/journal.pone.0074262	Chia-Yi Wu; Chin-Kuo Chang; Debbie Robson; Richard Jackson; Shaw-Ji Chen; Richard D. Hayes; Robert Stewart	2013	PLOS ONE (Journal)	PLOS

Workman 2024	A Comparison of Veterans with Problematic Opioid Use Identified through Natural Language Processing of Clinical Notes versus Using Diagnostic Codes	Opioids	Rule-based; Conventional Machine Learning	10.3390/healthcare12070799	Terri Elizabeth Workman; Joel Kupersmith; Phillip Ma; Christopher Spevak; Friedhelm Sandbrink; Yan Cheng; Qing Zeng-Treitler	2024	Healthcare (Journal)	MDPI
Vydiswaran 2024	Automated-detection of risky alcohol use prior to surgery using natural language processing	Alcohol	Rule-based	10.1111/acer.15222	V. G. Vinod Vydiswaran; Asher Strayhorn; Katherine Weber; Haley Stevens; Jessica Mellinger; G. Scott Winder; Anne C. Fernandez	2024	Alcohol: Clinical and Experimental Research (Journal)	Wiley
To 2020	Validation of an alcohol misuse classifier in hospitalized patients	Alcohol	Rule-based; Conventional Machine Learning	10.1016/j.alcohol.2019.09.008	Daniel To; Brihat Sharma; Niranjana Karnik; Cara Joyce; Dmitriy Dligach; Majid Afshar	2020	Alcohol (Journal)	Elsevier
Thompson 2021	Bias and fairness assessment of a natural language processing opioid misuse classifier: detection and mitigation of electronic health record data disadvantages across racial subgroups	Opioids	Deep Learning (RNN, LSTM, GRU,)	10.1093/jamia/ocab148	Hale M Thompson; Brihat Sharma; Sameer Bhalla; Randy Boley; Connor McCluskey; Dmitriy Dligach; Matthew M Churpek; Niranjana S Karnik; Majid Afshar	2021	JAMIA (Journal)	OUP
Tavabi 2023	Disparities in cannabis use and documentation in electronic health records among children and young adults	Cannabis	Rule-based; Large Language Models (LLMs) / Transformer Based Models	10.1038/s41746-023-00885-w	Nazgol Tavabi; Mariam Raza; Mallika Singh; Shahriar Golchin; Harsev Singh; Grant D. Hogue; Ata M. Kiapour	2023	npj Digital Medicine (Journal)	Springer Nature
Singleton 2023	Using natural language processing to identify opioid use disorder in electronic health record data	Opioids	Rule-based	10.1016/j.ijmedinf.2022.104963	Jade Singleton; Chengxi Li; Peter D. Akpunonu; Erin L. Abner; Anna M. Kucharska-Newton	2023	International Journal of Medical Informatics (Journal)	Elsevier
Sharma 2020	Publicly available machine learning models for identifying opioid misuse from the clinical notes of hospitalized patients	Opioids	Rule-based; Conventional Machine Learning; Deep Learning (RNN,	10.1186/s12911-020-1099-y	Brihat Sharma; Dmitriy Dligach; Kristin Swope; Elizabeth Salisbury-Afshar; Niranjana S. Karnik;	2020	BMC Medical Informatics and Decision Making (Journal)	Springer Nature

			LSTM, GRU,)		Cara Joyce; Majid Afshar			
Seng 2024	Tracking persistent postoperative opioid use: a proof-of-concept study demonstrating a use case for natural language processing	Opioids	Rule-based; Deep Learning (RNN, LSTM, GRU,); Large Language Models (LLMs) / Transformer Based Models	10.1136/rapm-2023-104629	Eri C Seng; Soraya Mehdipour; Sierra Simpson; Rodney A Gabriel	2024	Regional Anesthesia & Pain Medicine (Journal)	BMJ
Schirle 2021	Two data-driven approaches to identifying the spectrum of problematic opioid use: A pilot study within a chronic pain cohort	Opioids	Conventional Machine Learning	10.1016/j.ijmedinf.2021.104621	Lori Schirle; Alvin Jeffery; Ali Yaqoob; Sandra Sanchez-Roige; David C. Samuels	2021	International Journal of Medical Informatics (Journal)	Elsevier
Savova 2008	Mayo clinic NLP system for patient smoking status identification	Tobacco	Conventional Machine Learning	10.1197/jamia.M2437	G. K. Savova; P. V. Ogren; P. H. Duffy; J. D. Buntrock; C. G. Chute	2008	JAMIA (Journal)	OUP
Ruckdeschel 2023	Unstructured Data Are Superior to Structured Data for Eliciting Quantitative Smoking History From the Electronic Health Record	Tobacco	Rule-based; Conventional Machine Learning; Deep Learning (RNN, LSTM, GRU,); Large Language Models (LLMs) / Transformer Based Models	10.1200/CCI.22.00155	John C. Ruckdeschel; Mark Riley; Sriram Parsatharathy; Rajesh Chamarthi; Chakethraman Rajagopal; Hui Shuang Hsu; Doug Mangold; Chiny Driscoll	2023	JCO Clinical Cancer Informatics (Journal)	ASCO
Ridgway 2021	Natural Language Processing of Clinical Notes to Identify Mental Illness and Substance Use Among People Living with HIV: Retrospective Cohort Study	Alcohol; Opioids; Cocaine; Polysubstance use	Rule-based	10.2196/23456	Jessica P Ridgway; Arno Uvin; Jessica Schmitt; Tomasz Oliwa; Ellen Almirol; Samantha Devlin; John Schneider	2021	JMIR Medical Informatics (Journal)	JMIR
Richie 2023	Extracting social determinants of health events with transformer-based multitask, multilabel named entity recognition	Alcohol; Tobacco; Any Substance Not Otherwise Specified	Deep Learning (RNN, LSTM, GRU,); Large Language Models (LLMs) / Transformer Based Models	10.1093/jamia/ocad046	Russell Richie; Victor M Ruiz; Sifei Han; Lingyun Shi; Fuchiang (Rich) Tsui	2023	JAMIA (Journal)	OUP

Regan 2016	Determinants of Smoking and Quitting in HIV-Infected Individuals	Tobacco	Rule-based	10.1371/journal.pone.0153103	Regan S; Meigs JB; Grinspoon SK; Triant VA	2016	PLOS ONE (Journal)	PLOS
Poulsen 2022	Classifying Characteristics of Opioid Use Disorder From Hospital Discharge Summaries Using Natural Language Processing	Opioids	Large Language Models (LLMs) / Transformer Based Models	10.3389/fpubh.2022.850619	Melissa N. Poulsen; Philip J. Freda; Vanessa Troiani; Anahita Davoudi; Danielle L. Mowery	2022	Frontiers in Public Health (Journal)	Frontiers
Patel 2018	Leveraging Electronic Dental Record Data to Classify Patients Based on Their Smoking Intensity	Tobacco	Conventional Machine Learning	10.1055/s-0039-1681088	J. Patel; Z. Siddiqui; A. Krishnan; T. Thyvalikakath	2018	Methods of Information in Medicine (Journal)	Thieme
Palmer 2019a	Assessing data availability and quality within an electronic health record system through external validation against an external clinical data source	Tobacco	Rule-based	10.1186/s12911-019-0864-2	Ellen L. Palmer; John Higgins; Saeed Hassanpour; James Sargent; Christina M. Robinson; Jennifer A. Doherty; Tracy Onega	2019	BMC Medical Informatics and Decision Making (Journal)	Springer Nature
Palmer 2019b	Building a tobacco user registry by extracting multiple smoking behaviors from clinical notes	Tobacco	Conventional Machine Learning	10.1186/s12911-019-0863-3	Ellen L. Palmer; Saeed Hassanpour; John Higgins; Jennifer A. Doherty; Tracy Onega	2019	BMC Medical Informatics and Decision Making (Journal)	Springer Nature
Ni 2021	Automated detection of substance use information from electronic health records for a pediatric population	Alcohol; Opioids; Cannabis; Tobacco	Rule-based; Conventional Machine Learning; Deep Learning (RNN, LSTM, GRU,)	10.1093/jamia/ocab116	Yizhao Ni; Alycia Bachtel; Katie Nause; Sarah Beal	2021	JAMIA (Journal)	OUP
Miranda 2024	DeepBiomarker2: Prediction of Alcohol and Substance Use Disorder Risk in Post-Traumatic Stress Disorder Patients Using Electronic Medical Records and Multiple Social Determinants of Health	Alcohol	Deep Learning (RNN, LSTM, GRU,)	10.3390/jpm14010094	Oshin Miranda; Peihao Fan; Xiguang Qi; Haohan Wang; M. Daniel Brannock; Thomas R. Kosten; Neal David Ryan; Levent Kirisci; Lirong Wang	2024	Journal of Personalized Medicine (Journal)	MDPI
McDermott 2023	Using Natural Language Processing and Machine Learning to Identify Opioids in Electronic Health Record Data	Opioids	Conventional Machine Learning	10.2147/JPR.S389160	Sean P McDermott; Ajay D Wasan	2023	Journal of Pain Research (Journal)	Taylor & Francis

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Manca 2021	Estimating the Burden of Alcohol on Ambulance Callouts through Development and Validation of an Algorithm Using Electronic Patient Records	Alcohol	Conventional Machine Learning	10.3390/ijerph18126363	Francesco Manca; Jim Lewsey; Ryan Waterson; Sarah M. Kernaghan; David Fitzpatrick; Daniel Mackay; Colin Angus; Niamh Fitzgerald	2021	International Journal of Environmental Research and Public Health (Journal)	MDPI
Lybarger 2023	Leveraging natural language processing to augment structured social determinants of health data in the electronic health record	Alcohol; Tobacco	Deep Learning (RNN, LSTM, GRU,); Large Language Models (LLMs) / Transformer Based Models	10.1093/jamia/ocad073	Kevin Lybarger; Nicholas J Dobbins; Ritche Long; Angad Singh; Patrick Wedgeworth; Özlem Uzuner; Meliha Yetisgen	2023	JAMIA (Journal)	OUP
Liu 2023	Leveraging natural language processing to identify eligible lung cancer screening patients with the electronic health record	Tobacco	Rule-based	10.1016/j.ijmedinf.2023.105136	Siru Liu; Allison B. McCoy; Melinda C. Aldrich; Kim L. Sandler; Thomas J. Reese; Bryan Steitz; Jiang Bian; Yonghui Wu; Elise Russo; Adam Wright	2023	International Journal of Medical Informatics (Journal)	Elsevier
Lin 2022	External validation of a machine learning classifier to identify unhealthy alcohol use in hospitalized patients	Alcohol	Conventional Machine Learning	10.1111/add.15730	Yiqi Lin; Brihat Sharma; Hale M. Thompson; Randy Boley; Kathryn Perticone; Neeraj Chhabra; Majid Afshar; Niranjana S. Karnik	2022	Addiction (Journal)	Wiley
Kim 2023	Identifying Alcohol-Related Information From Unstructured Bilingual Clinical Notes With Multilingual Transformers	Alcohol	Conventional Machine Learning; Large Language Models (LLMs) / Transformer Based Models	10.1109/ACCESS.2023.3245523	Han Kyul Kim; Yujin Park; Yeju Park; Eunji Choi; Sodam Kim; Haehyun You; Ye Seul Bae	2023	IEEE Access (Journal)	IEEE
Keyhani 2018	A search algorithm for identifying likely users and non-users of marijuana from the free text of the electronic medical record	Cannabis	Rule-based	10.1371/journal.pone.0193706	Salomeh Keyhani; Marzieh Vali; Beth Cohen; Alexandra Woodbridge; Melanie Arenson; Elnaz	2018	PLOS ONE (Journal)	PLOS

					Eilkhani; Christina Aivadyan; Deborah Hasin			
Kashyap 2023	A deep learning method to detect opioid prescription and opioid use disorder from electronic health records	Opioids	Deep Learning (RNN, LSTM, GRU,)	10.1016/j.ijmedinf.2022.104979	Aditya Kashyap; Chris Callison-Burch; Mary Regina Boland	2023	International Journal of Medical Informatics (Journal)	Elsevier
Hutto 2024	Using a natural language processing toolkit to classify electronic health records by psychiatric diagnosis	Alcohol; Opioids; Cannabis; Polysubstance use	Rule-based; Conventional Machine Learning	10.1177/14604582241296411	Alissa Hutto; Tarek M Zikry; Buck Bohac; Terra Rose; Jasmine Staebler; Janet Slay; C Ray Cheever; Michael R Kosorok; Rebekah P. Nash	2024	Health Informatics Journal (Journal)	SAGE
Hegde 2018	Tobacco use status from clinical notes using Natural Language Processing and rule based algorithm	Tobacco	Rule-based	10.3233/THC-171127	Harshad Hegde; Neel Shimpi; Ingrid Glurich; Amit Acharya	2018	Technology and Health Care (Journal)	IOS Press
Hazlehurst 2019	Using natural language processing of clinical text to enhance identification of opioid-related overdoses in electronic health records data	Any Substance Not Otherwise Specified	Rule-based	10.1002/pds.4810	Brian Hazlehurst; Carla A. Green; Nancy A. Perrin; John Brandes; David S. Carrell; Andrew Baer; Angela DeVeaugh-Geiss; Paul M. Coplan	2019	Pharmacoepidemiology and Drug Safety (Journal)	Wiley
Haller 2017	Enhancing Risk Assessment in Patients Receiving Chronic Opioid Analgesic Therapy Using Natural Language Processing	Opioids	Rule-based	10.1093/pm/pnw283	Irina V. Haller; Colleen M. Renier; Mitch Juusola; Paul Hitz; William Steffen; Michael J. Asmus; Terri Craig; Jack Mardekian; Elizabeth T. Masters; Thomas E. Elliott	2017	Pain Medicine (Journal)	OUP
Groenhof 2020	Data mining information from electronic health records produced high yield and accuracy for current smoking status	Tobacco	Rule-based	10.1016/j.jclinepi.2019.11.006	Groenhof TKJ; Koers LR; Blasse E, de Groot M; Grobbee DE; Bots ML; Asselbergs FW; Lely AT; Haitjema S; UPOD; UCC-CVRM Study Groups.	2020	Journal of Clinical Epidemiology (Journal)	Elsevier

Green 2019	Identifying and classifying opioid-related overdoses: A validation study	Opioids	Conventional Machine Learning	10.1002/pds.4772	Carla A. Green; Nancy A. Perrin; Brian Hazlehurst; Shannon L. Janoff; Angela DeVeaugh-Geiss; David S. Carrell; Carlos G. Grijalva; Caihua Liang; Cheryl L. Enger; Paul M. Coplan	2019	Pharmacoepidemiology and Drug Safety (Journal)	Wiley
Feller 2020	Detecting Social and Behavioral Determinants of Health with Structured and Free-Text Clinical Data	Alcohol; Opioids; Cannabis; Cocaine; Amphetamines; Any Substance Not Otherwise Specified	Conventional Machine Learning	10.1055/s-0040-1702214	Daniel J. Feller; Oliver J. Bear Don't Walk IV; Jason Zucker; Michael T. Yin; Peter Gordon; Noémie Elhadad	2020	Applied Clinical Informatics (Journal)	Thieme
Ebrahimi 2024	Identification of patients' smoking status using an explainable AI approach: a Danish electronic health records case study	Tobacco	Large Language Models (LLMs) / Transformer Based Models	10.1186/s12874-024-02231-4	Ali Ebrahimi; Margrethe Bang Høstgaard Henriksen; Claus Lohman Brasen; Ole Hilberg; Torben Frøstrup Hansen; Lars Henrik Jensen; Abdolrahman Peimankar; Uffe Kock Wiil	2024	BMC Medical Research Methodology (Journal)	Springer Nature
deBoer 2022	Data mining to retrieve smoking status from electronic health records in general practice	Tobacco	Rule-based	10.1093/ehjdh/ztac031	Annemarijn R de Boer; Mark C H de Groot; T Katrien J Groenhof; Sander van Doorn; Ilonca Vaartjes; Michiel L Bots; Saskia Haitjema	2022	European Heart Journal – Digital Health (Journal)	OUP
Carrell 2022	Clinical documentation of patient-reported medical cannabis use in primary care: Toward scalable extraction using natural language processing methods	Cannabis	Rule-based; Conventional Machine Learning	10.1080/08897077.2021.1986767	David S. Carrell; David J. Cronkite; Mary Shea; Malia Oliver; Casey Luce; Theresa E. Matson; Jennifer F. Bobb; Clarissa Hsu; Ingrid A. Binswanger;	2022	Substance Abuse (Journal)	Taylor & Francis

					Kendall C. Browne; Andrew J. Saxon; Jennifer McCormack; Eve Jelstrom; Udi E. Ghitza; Cynthia I. Campbell; Katharine A. Bradley; Gwen T. Lapham			
Caccamisi 2020	Natural language processing and machine learning to enable automatic extraction and classification of patients' smoking status from electronic medical records	Tobacco	Rule-based; Conventional Machine Learning	10.1080/03009734. 2020.1792010	Andrea Caccamisi; Leif Jørgensen; Hercules Dalianis; Mats Rosenlund	2020	Upsala Journal of Medical Sciences (Journal)	Taylor & Francis
Bae 2021	Keyword Extraction Algorithm for Classifying Smoking Status from Unstructured Bilingual Electronic Health Records Based on Natural Language Processing	Tobacco	Rule-based; Conventional Machine Learning	10.3390/app11198 812	Ye Seul Bae; Kyung Hwan Kim; Han Kyul Kim; Sae Won Choi; Taehoon Ko; Hee Hwa Seo; Hae-Young Lee; Hyojin Jeon	2021	Applied Sciences (Journal)	MDPI
Badger 2019	Machine learning for phenotyping opioid overdose events	Opioids	Conventional Machine Learning	10.1016/j.jbi.2019. 103185	Jonathan Badger; Eric LaRose; John Mayer; Fereshteh Bashiri; David Page; Peggy Peissig	2019	Journal of Biomedical Informatics (Journal)	Elsevier
Arribas 2024	A transdiagnostic prodrome for severe mental disorders: an electronic health record study	Cannabis; Cocaine; Tobacco	Conventional Machine Learning	10.1038/s41380- 024-02533-5	Maite Arribas; Dominic Oliver; Rashmi Patel; Daisy Kornblum; Hitesh Shetty; Stefano Damiani; Kamil Krakowski; Umberto Provenzano; Daniel Stahl; Nikolaos Koutsouleris; Philip McGuire; Paolo Fusar- Poli	2024	Molecular Psychiatry (Journal)	Springer Nature
Alzubi 2022	Automated Detection of Substance-Use Status and Related Information from Clinical Text	Alcohol; Tobacco; Any Substance Not Otherwise Specified	Rule-based	10.3390/s22249609	Raid Alzubi; Hadeel Alzoubi; Stamos Katsigiannis; Daune West; Naeem Ramzan	2022	Sensors (Journal)	MDPI

Afshar 2022	Development and multimodal validation of a substance misuse algorithm for referral to treatment using artificial intelligence (SMART-AI): a retrospective deep learning study	Alcohol; Opioids; Other: non-opioid drug misuse	Conventional Machine Learning; Deep Learning (RNN, LSTM, GRU,)	10.1016/S2589-7500(22)00041-3	Majid Afshar; Brihat Sharma; Dmitriy Dligach; Madeline Oguss; Randall Brown; Neeraj Chhabra; Hale M Thompson; Talar Markossian; Cara Joyce; Matthew M Churpek; Niranjana S Karnik	2022	The Lancet Digital Health (Journal)	Elsevier
Afshar 2021	External validation of an opioid misuse machine learning classifier in hospitalized adult patients	Opioids	Deep Learning (RNN, LSTM, GRU,)	10.1186/s13722-021-00229-7	Majid Afshar; Brihat Sharma; Sameer Bhalla; Hale M. Thompson; Dmitriy Dligach; Randy A. Boley; Ekta Kishen; Alan Simmons; Kathryn Perticone; Niranjana S. Karnik	2021	Addiction Science & Clinical Practice (Journal)	Springer Nature
Afshar 2019a	Natural language processing and machine learning to identify alcohol misuse from the electronic health record in trauma patients: development and internal validation	Alcohol	Rule-based; Conventional Machine Learning	10.1093/jamia/ocy166	Majid Afshar; Andrew Phillips; Niranjana Karnik; Jeanne Mueller; Daniel To; Richard Gonzalez; Ron Price; Richard Cooper; Cara Joyce; Dmitriy Dligach	2019	JAMIA (Journal)	OUP
Afshar 2019b	Subtypes in patients with opioid misuse: A prognostic enrichment strategy using electronic health record data in hospitalized patients	Opioids; Cocaine	Rule-based; Conventional Machine Learning	10.1371/journal.pone.0219717	Majid Afshar; Cara Joyce; Dmitriy Dligach; Brihat Sharma; Robert Kania; Meng Xie; Kristin Swope; Elizabeth Salisbury-Afshar; Niranjana S. Karnik	2019	PLOS ONE (Journal)	PLOS
Afshar 2023	Deployment of Real-time Natural Language Processing and Deep Learning Clinical Decision Support in the Electronic Health Record: Pipeline Implementation for an Opioid Misuse Screener in Hospitalized Adults	Opioids	Conventional Machine Learning	10.2196/44977	Majid Afshar; Sabrina Adelaide; Felice Resnik; Marlon P Mundt; John Long; Margaret Leaf; Theodore Ampian; Graham J Wills; Benjamin Schnapp; Michael Chao; Randy Brown; Cara Joyce; Brihat Sharma; Dmitriy	2023	JMIR Medical Informatics (Journal)	JMIR

PART 2. Citation Matching and Threshold Selection

Title-based matching used a Jaccard word-overlap criterion. An initial 60% title-word-overlap screen generated candidate pairs; exact matches were accepted automatically, and non-identical candidates were adjudicated for study identity by consensus using title, author, journal, year, and formatting context. To evaluate possible false negatives, candidate pairs were re-examined across the 20–60% range. Matching used consensus adjudication rather than independent double-coding, so an inter-rater agreement statistic was not computed.

Match composition. Of 2,287 confirmed matches, 1,990 (87.0%) were exact title matches and 297 (13.0%) were accepted by consensus after manual review. Of the 354 non-exact candidates from the initial 60% screen, 276 were accepted and 78 (22.0%) rejected as different studies sharing substantial title vocabulary. The 20–60% sweep confirmed 21 further matches but no additional gold-standard study.

Threshold validation. Genuine same-study matches continued to appear down to 42.9% and none below it, whereas the 20–40% bands contained only different-study pairs; 40% was therefore adopted as the operational threshold and applied uniformly to all platforms. The false-negative rate of the procedure, the proportion of retrieval events in which a genuine match would have been scored as a miss under exact or 60%-screen matching because the title differed only in formatting, was 0.38–1.14%. None of the 10 never-retrieved studies was matched at any overlap down to 20%.

Table S3. Overlap-band sweep establishing the 40% operational matching threshold (20-60% Jaccard overlap).

Overlap band	Candidate pairs admitted	Genuine same-study matches	Cumulative candidates
[50, 60%)	556	15	556
[40, 50%)	1,599	6	2,155
[30, 40%)	2,908	0	5,063
[20, 30%)	4,752	0	9,815

Notes. Candidate pairs rose steeply as the threshold was lowered, but genuine same-study matches were confined entirely to the 40-60% range; no genuine match scored below 42.9%, and none of the 10 never-retrieved studies was matched at any threshold down to 20%. Lowering the threshold below 40% therefore yields no additional genuine match while admitting thousands of different-study pairs, so 40% is retained as the operational threshold. The complete candidate-level adjudication is provided in full as as Supplementary Data 1.

Threshold sensitivity of the 40% Jaccard matching cutoff

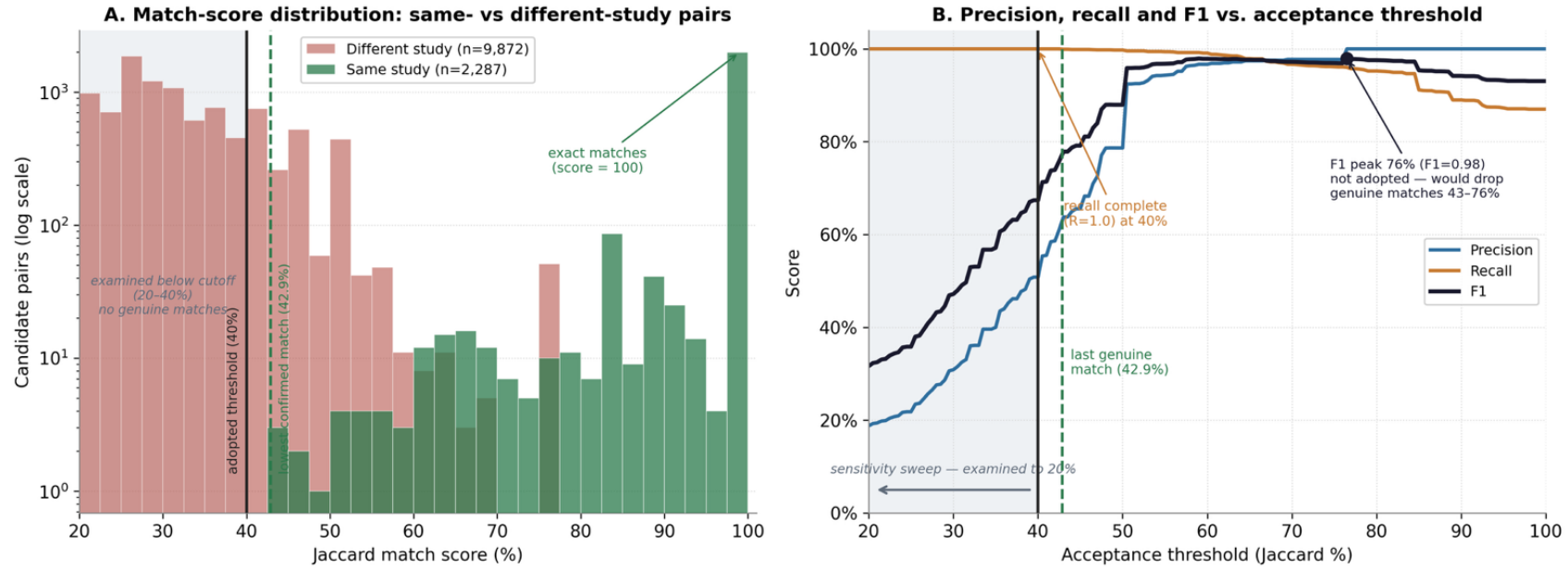


Figure S1. Empirical determination of the title-overlap matching threshold.

(a) Distribution of Jaccard title-overlap scores across all candidate comparisons, with confirmed same-study matches shown separately from different-study pairs. (b) Matching precision, recall, and F1 across candidate acceptance thresholds from 20% to 100%. The two score distributions separate at 40% overlap — the adopted 40% operational threshold (marked), calibrated from an initial 60% candidate screen and a 20–60% sensitivity sweep. Genuine same-study matches extended down to 42.9% and none scored below 40%, so the 40% cutoff sits just below the lowest confirmed match and preserves complete recall of genuine matches (recall = 1.0 at the cutoff); overlaps below 40% corresponded only to different-study pairs, which were adjudicated but yielded no additional matches. F1 is maximized at a higher threshold, but adopting that value would exclude genuine matches between 42.9% and the F1 peak; 40% was therefore retained so that lowering it adds only review burden, never a missed true match. Scores are pooled across all 225 executions and five platforms; see Table S3 for the band-level sweep.

Supplementary Data 1. Candidate-level matching dataset.

Every candidate LLM-returned record evaluated against the 83-study gold standard across the 225 experimental executions (5 platforms × 5 prompting strategies × 3 formulations × 3 runs), provided as a separate Excel file. One row is one candidate pair: a title returned by a platform alongside the gold-standard study it was compared with, the title-overlap score between them, and the adjudication outcome. Sheet 01 contains the primary matching analysis at the 60% operational screen (n = 2,344 candidate pairs); Sheet 02 contains the 20–60% threshold-sensitivity sweep reported in Table S3 and Figure S1 (n = 9,815). Match score is the Jaccard similarity of the two titles' word sets, computed on the literal words returned by the platform. Bibliographic fields describe the gold-standard study (Table S2).

PART 3. Platform Retrieval Performance

Two complementary levels of analysis are reported throughout. Formulation-level recall — the proportion of gold-standard studies returned by a single query formulation (pooled across its three runs) — is the primary metric, reflecting what a typical user query returns and the unit of experience most directly relevant to clinical and research practice. Platform-level pooled recall — the proportion of gold-standard studies retrieved at least once across all 15 formulations and runs — is the comparative benchmarking metric, characterising each platform’s retrieval capacity. Their difference quantifies evidence within each platform’s reach that is unlikely to surface from any given query.

Analytic Framework

A1.1 Experimental Structure

Five platforms were evaluated using 15 prompt formulations (5 strategies × 3 variations), each executed in three independent runs, yielding 225 total query executions (5 × 15 × 3). The evaluation used an 83-study gold standard compiled before platform testing and not publicly available at time of evaluation.

Table S4. Experimental design summary and inference units.

Component	Levels	Replications	Metric computed at	Unit used for statistical test
Platforms	5	—	Platform × formulation; platform pooled	Compared via matched units below
Prompt formulations	15 (strategy × variation)	3 runs each	Formulation-level after pooling across runs	Formulation (n=15) for Friedman tests; study (n=83) for Cochran's Q
Gold-standard studies	83	Fixed	Study-level binary 'ever retrieved' per platform	Study (n=83) for Cochran's Q (secondary capacity benchmark)

A1.2 Metric Operationalization

A1.2.1 Recall (formulation-level, pooled across runs). For platform p and formulation f , let $M(p,f,r)$ be the set of gold-standard studies matched in run $r \in \{1,2,3\}$. The pooled matched set is: $M(p,f)U = M(p,f,1) \cup M(p,f,2) \cup M(p,f,3)$. Formulation-level recall = $|M(p,f)U| / 83$. For few-shot formulations, in-context example studies were excluded from the denominator and numerator to prevent artificial inflation of recall estimates.

A1.2.2 Precision (screening-burden proxy). Let $R(p,f,r)$ be the set of retrieved items in run r . The pooled deduplicated retrieved set is: $R(p,f)U = R(p,f,1) \cup R(p,f,2) \cup R(p,f,3)$. Precision = $|M(p,f)U| / |R(p,f)U|$. If $|R(p,f)U| = 0$, precision is set to 0. Precision approximates the irrelevant material a user would need to screen to identify relevant studies — the higher the precision, the lower the screening burden.

A1.2.3 Inter-run consistency (mean pairwise Jaccard similarity). Consistency was computed on matched sets $M(p,f,1)$, $M(p,f,2)$, $M(p,f,3)$ using mean pairwise Jaccard similarity across the three pairs ($R1-R2$, $R1-R3$, $R2-R3$). Consistency = 0 indicates complete non-overlap between runs under identical conditions; consistency = 1.00 indicates perfect reproduction across runs.

A1.2.4 Single-query zero-retrieval probability (per formulation; new metric). For a given evidence domain D and platform p , the zero-retrieval probability is the proportion of the 15 formulations for which no gold-standard study from D was retrieved: $P(\text{zero}|D,p) = (\text{number of formulations } f \text{ for which } |M(p,f)U \cap D| = 0) / 15$. The complement, $1 - P(\text{zero}|D,p)$, is the probability that a typical single query returns at least one relevant study from domain D . This metric is one of the two primary user-facing outcomes, reported by evidence domain alongside formulation-level recall.

A1.3 Statistical Tests

A1.3.1 Platform-level pooled recall: Cochran's Q + Bonferroni McNemar. Each gold-standard study s was treated as a paired binary outcome per platform: $Y(s,p) = 1$ if study s was retrieved at least once by platform p across any of its 15 formulations and 3 runs; 0 otherwise. This produces an 83×5 paired binary matrix analyzed by Cochran's Q (two-tailed). When significant, 10 pairwise McNemar tests were conducted with Bonferroni correction ($\alpha = 0.005$ per comparison).

A1.3.2 Formulation-level recall, precision, and consistency: Friedman + FDR Wilcoxon. Recall, precision, consistency, and F1-score were compared across platforms using 15 prompt formulations as matched repeated-measures units (15×5 matrices). Friedman tests (two-tailed) were followed by 10 pairwise Wilcoxon signed-rank tests with Benjamini–Hochberg FDR correction ($\alpha = 0.05$). P-values reported in the main text reflect FDR-corrected values.

A1.3.3 Domain-level zero-retrieval probability: Cochran's Q + Bonferroni McNemar. For each evidence domain, platforms were compared in the proportion of formulations returning zero domain-specific studies. Each formulation was treated as a binary matched observation (zero retrieval = 1; any retrieval = 0), yielding a 15×5 matrix per domain analyzed by Cochran's Q. When significant, 10 pairwise McNemar tests with Bonferroni correction ($\alpha = 0.005$) identified which platform pairs differed. All tests two-tailed, $\alpha = 0.05$.

A1.3.4 Publication characteristics and retrieval failure: Fisher's exact + FDR. Associations between publication characteristics (publisher, venue type, publication year) and retrieval failure were assessed using Fisher's exact tests (two-tailed), with Benjamini–Hochberg FDR correction within each characteristic family. Two outcomes were evaluated: (i) overall non-retrieval (never retrieved by any platform under any condition) and (ii) platform-specific non-retrieval.

Table S5. Complete performance metrics for all 75 platform–strategy–variation combinations, ranked by F1-score.

Rank	Platform	Strategy	Variation	Recall	Precision	F1	Consistency	Matched studies	Total retrieved	Level
1	ChatGPT	Few-Shot	V2	0.289	0.558	0.381	0.431	24	43	Form.
2	ChatGPT	Few-Shot	V0	0.265	0.478	0.341	0.307	22	46	Form.
3	Claude	Few-Shot	V2	0.253	0.477	0.331	0.471	21	44	Form.
4	Gemini	Zero-Shot	V2	0.205	0.607	0.306	0.146	17	28	Form.
5	Ai2	PICO	V1	0.494	0.180	0.264	0.739	41	228	Form.
6	Ai2	PICO	V0	0.434	0.187	0.261	0.691	36	193	Form.
7	Gemini	Zero-Shot	V1	0.241	0.286	0.261	0.234	20	70	Form.
8	Claude	Persona	V1	0.181	0.417	0.252	0.232	15	36	Form.
9	Ai2	CoT	V2	0.253	0.250	0.251	0.937	21	84	Form.
10	Ai2	CoT	V1	0.277	0.219	0.245	0.768	23	105	Form.
11	Claude	Persona	V2	0.157	0.433	0.230	0.277	13	30	Form.
12	Gemini	Zero-Shot	V0	0.169	0.350	0.228	0.274	14	40	Form.
13	Ai2	Few-Shot	V1	0.446	0.147	0.222	0.706	37	251	Form.
14	Ai2	CoT	V0	0.217	0.225	0.221	0.963	18	80	Form.
15	Ai2	Persona	V0	0.458	0.144	0.219	0.757	38	264	Form.
16	Ai2	PICO	V2	0.422	0.141	0.211	0.757	35	248	Form.
17	ChatGPT	Persona	V0	0.145	0.375	0.209	0.208	12	32	Form.
18	Ai2	Few-Shot	V0	0.446	0.131	0.202	0.689	37	283	Form.
19	ChatGPT	Few-Shot	V1	0.157	0.277	0.200	0.607	13	47	Form.
20	Ai2	Persona	V1	0.398	0.131	0.197	0.714	33	252	Form.
21	Claude	Few-Shot	V1	0.133	0.333	0.190	0.331	11	33	Form.
22	Ai2	Zero-Shot	V0	0.422	0.118	0.184	0.701	35	297	Form.
23	Claude	PICO	V0	0.157	0.217	0.182	0.308	13	60	Form.
24	Ai2	Few-Shot	V2	0.398	0.117	0.181	0.704	33	281	Form.

Rank	Platform	Strategy	Variation	Recall	Precision	F1	Consistency	Matched studies	Total retrieved	Level
25	Consensus	CoT	V1	0.193	0.167	0.179	1.000	16	96	Form.
26	Consensus	CoT	V2	0.193	0.160	0.175	1.000	16	100	Form.
27	ChatGPT	Persona	V2	0.120	0.323	0.175	0.275	10	31	Form.
28	Consensus	CoT	V0	0.241	0.136	0.174	0.700	20	147	Form.
29	Ai2	Persona	V2	0.386	0.108	0.168	0.780	32	297	Form.
30	Ai2	Zero-Shot	V1	0.506	0.100	0.167	0.593	42	419	Form.
31	Consensus	PICO	V0	0.289	0.114	0.163	0.167	24	211	Form.
32	Consensus	Zero-Shot	V1	0.301	0.104	0.154	0.112	25	241	Form.
33	Consensus	PICO	V2	0.253	0.108	0.151	0.296	21	195	Form.
34	Claude	Persona	V0	0.096	0.333	0.150	0.500	8	24	Form.
35	ChatGPT	Zero-Shot	V2	0.108	0.231	0.148	0.241	9	39	Form.
36	Consensus	PICO	V1	0.265	0.102	0.147	0.133	22	216	Form.
37	Ai2	Zero-Shot	V2	0.398	0.086	0.141	0.713	33	384	Form.
38	Claude	Zero-Shot	V0	0.084	0.389	0.139	0.619	7	18	Form.
39	Consensus	Persona	V2	0.193	0.105	0.136	0.738	16	152	Form.
40	ChatGPT	Zero-Shot	V0	0.096	0.216	0.133	0.000	8	37	Form.
41	Claude	Few-Shot	V0	0.084	0.304	0.132	0.333	7	23	Form.
42	ChatGPT	PICO	V1	0.133	0.126	0.129	0.000	11	87	Form.
43	ChatGPT	Persona	V1	0.084	0.259	0.127	0.429	7	27	Form.
44	Claude	PICO	V1	0.084	0.259	0.127	0.454	7	27	Form.
45	Claude	Zero-Shot	V1	0.072	0.429	0.124	0.444	6	14	Form.
46	Gemini	PICO	V2	0.229	0.084	0.123	0.188	19	225	Form.
47	Gemini	PICO	V1	0.096	0.167	0.122	0.359	8	48	Form.
48	Gemini	PICO	V0	0.145	0.103	0.121	0.258	12	116	Form.
49	Consensus	Persona	V1	0.133	0.110	0.120	1.000	11	100	Form.
50	Claude	PICO	V2	0.145	0.098	0.117	0.498	12	122	Form.
51	ChatGPT	PICO	V2	0.096	0.143	0.115	0.125	8	56	Form.
52	Gemini	Few-Shot	V2	0.096	0.131	0.111	0.827	8	61	Form.
53	Consensus	Zero-Shot	V0	0.217	0.065	0.100	0.039	18	277	Form.

Rank	Platform	Strategy	Variation	Recall	Precision	F1	Consistency	Matched studies	Total retrieved	Level
54	Consensus	Persona	V0	0.108	0.092	0.099	1.000	9	98	Form.
55	ChatGPT	Zero-Shot	V1	0.060	0.238	0.096	0.333	5	21	Form.
56	ChatGPT	PICO	V0	0.096	0.089	0.092	0.000	8	90	Form.
57	Gemini	CoT	V2	0.048	0.500	0.088	0.000	4	8	Form.
58	Claude	CoT	V0	0.048	0.444	0.087	0.000	4	9	Form.
59	Claude	CoT	V2	0.048	0.444	0.087	0.639	4	9	Form.
60	Gemini	Few-Shot	V0	0.072	0.094	0.082	0.289	6	64	Form.
61	Gemini	Few-Shot	V1	0.072	0.091	0.081	0.333	6	66	Form.
62	Claude	Zero-Shot	V2	0.048	0.200	0.078	1.000	4	20	Form.
63	ChatGPT	CoT	V1	0.036	0.333	0.065	0.167	3	9	Form.
64	Gemini	CoT	V1	0.036	0.333	0.065	0.333	3	9	Form.
65	Claude	CoT	V1	0.036	0.158	0.059	0.333	3	19	Form.
66	Consensus	Zero-Shot	V2	0.060	0.050	0.055	1.000	5	100	Form.
67	Consensus	Few-Shot	V0	0.060	0.050	0.055	1.000	5	100	Form.
68	Consensus	Few-Shot	V2	0.060	0.050	0.055	1.000	5	100	Form.
69	Consensus	Few-Shot	V1	0.060	0.050	0.055	1.000	5	100	Form.
70	ChatGPT	CoT	V2	0.024	0.333	0.045	0.667	2	6	Form.
71	ChatGPT	CoT	V0	0.024	0.167	0.042	1.000	2	12	Form.
72	Gemini	Persona	V2	0.036	0.048	0.041	0.333	3	62	Form.
73	Gemini	CoT	V0	0.024	0.125	0.040	0.000	2	16	Form.
74	Gemini	Persona	V0	0.036	0.043	0.039	0.556	3	69	Form.
75	Gemini	Persona	V1	0.012	0.011	0.011	1.000	1	94	Form.

Notes. Each row represents one platform evaluated under one prompting strategy and one wording variation (V0–V2), with outputs aggregated across three independent runs. Recall = unique gold-standard studies matched across three runs / 83. Precision = unique matched studies / total unique retrieved across three runs (after deduplication). $F1 = 2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall})$. Consistency = mean pairwise Jaccard similarity across runs. Matched studies = unique gold-standard studies matched across three runs. Total retrieved = unique studies returned across three runs after deduplication. For Consensus, retrieval was restricted to the first 100 rank-ordered results per run. Level = formulation-level (Form.) throughout. Platforms differed significantly in formulation-level recall ($p < 0.001$), precision ($p < 0.001$), consistency ($p < 0.001$), and F1-score ($p < 0.05$). Post-hoc testing used Bonferroni-adjusted McNemar tests for pooled recall ($\alpha = 0.005$) and FDR-adjusted Wilcoxon signed-rank tests for formulation-level metrics ($\alpha = 0.05$). For few-shot formulations, in-context example studies were excluded from recall calculations.

Table S6. Pairwise comparisons of platform-level pooled recall.

Platform 1	Platform 2	Retrieved only by P1	Retrieved only by P2	McNemar χ^2	p-value
Ai2 Finder	ChatGPT-4.1	23	6	8.828	$p < 0.005$
Ai2 Finder	Claude-Sonnet-4.0	31	9	11.025	$p < 0.001$
Ai2 Finder	Gemini-2.5-Pro	26	8	8.500	$p < 0.005$
Ai2 Finder	Consensus	24	8	7.031	$p = 0.008$
Consensus	ChatGPT-4.1	16	15	0.000	$p = 1.00$
Consensus	Gemini-2.5-Pro	15	13	0.036	$p = 0.85$
Consensus	Claude-Sonnet-4.0	20	14	0.735	$p = 0.39$
ChatGPT-4.1	Gemini-2.5-Pro	10	9	1.000	$p = 1.00$
ChatGPT-4.1	Claude-Sonnet-4.0	12	7	5.000	$p = 0.36$
Gemini-2.5-Pro	Claude-Sonnet-4.0	11	7	4.000	$p = 0.48$

Notes. Pooled recall (a study retrieved at least once across a platform's 15 formulations and 3 runs) differed across platforms by Cochran's Q ($Q = 20.225$, $df = 4$, $p < 0.001$). Post-hoc pairwise comparisons used McNemar's test with Bonferroni correction across the 10 comparisons ($\alpha = 0.005$ per comparison). "Retrieved only by P1/P2" are the discordant counts. Ai2 Finder significantly exceeded ChatGPT-4.1, Claude-Sonnet-4.0, and Gemini-2.5-Pro; its advantage over Consensus was not significant after correction ($p = 0.008$). No comparison among the four non-Ai2 platforms was significant. Where discordant counts were small, an exact binomial McNemar test was used; the statistic column reports $|b - c|$ for those rows.

OUTPUT-VOLUME SENSITIVITY (Ai2 FINDER TOP-k)

Ai2 Finder returns longer ranked result lists than the other platforms. To assess whether its recall advantage depends on output volume, its recall was recomputed after truncating each run to the top 100 rank-ordered results, mirroring the 100-result cap already applied to Consensus in the primary analysis. Conversational platforms are unaffected: their output lengths fall below the cap.

Table S7. Ai2 Finder recall before and after the 100-result output cap.

Metric	Full output	Capped at 100
Mean formulation-level recall	39.7%	38.2%
Mean formulation-level precision	0.152	0.222
Output-length range (items per run)	71–217	100 (cap)
Formulations where the cap binds	12 of 15	—

Notes. Values are formulation-level and replicate-pooled: recall is the proportion of the 83 gold-standard studies matched by a formulation across its three runs, and precision the matched share of the deduplicated retrieved set. Recall is computed on the same matched sets as Table S6, so the fifteen per-

formulation values in Table S8 correspond one-to-one with the Ai2 Finder rows of that table. Formulations returning fewer than 100 items per run are unchanged by the cap. Capping reduced mean recall by 1.5 percentage points while raising mean precision from 0.152 to 0.222, indicating that most matched studies sat near the top of the ranked list rather than being dispersed through a long tail.

Table S8. Per-formulation Ai2 Finder recall, full vs capped output.

Formulation	Full output size	Recall (full)	Recall (capped)
1_1	217	50.6%	47.0%
1_0	169	42.2%	38.6%
5_2	150	42.2%	38.6%
3_0	195	45.8%	41.0%
1_2	213	39.8%	37.3%
4_0	71	21.7%	21.7%
4_1	77	27.7%	27.7%
2_1	137	44.6%	44.6%
4_2	78	25.3%	25.3%
2_0	176	44.6%	44.6%
3_1	146	39.8%	39.8%
5_1	141	49.4%	48.2%
5_0	122	43.4%	39.8%
2_2	170	39.8%	39.8%
3_2	176	38.6%	38.6%

Notes. Formulation IDs are strategy_variation codes. Capped recall applies the 100-result truncation per run before pooling.

Table S9. Platform summary: formulation-level and pooled recall, with precision and consistency distributions (n=15 formulations per platform).

Platform	Pooled recall (platform-level)	Median formulation recall	Recall range	Median precision	Median consistency	Best F1	Best F1 configuration	Pooled recall vs formulation median gap
Ai2 Finder	72.3% (60/83)	42.2%	21.7%–50.6%	14.1%	0.714	0.264	PICO V1	–30.1 pp
Consensus	53.0% (44/83)	19.3%	6.0%–30.1%	10.4%	1.000	0.179	CoT V1	–33.7 pp

Platform	Pooled recall (platform-level)	Median formulation recall	Recall range	Median precision	Median consistency	Best F1	Best F1 configuration	Pooled recall vs formulation median gap
ChatGPT-4.1	51.8% (43/83)	9.6%	2.4%–28.9%	25.9%	0.275	0.381	Few-Shot V2	–42.2 pp
Claude-Sonnet-4.0	45.8% (38/83)	8.4%	3.6%–25.3%	33.3%	0.444	0.331	Few-Shot V2	–37.4 pp
Gemini-2.5-Pro	50.6% (42/83)	7.2%	1.2%–24.1%	12.5%	0.289	0.306	Zero-Shot V2	–43.4 pp

Notes. 'Pooled recall' reflects the platform-level maximum: the proportion of the 83 gold-standard studies retrieved at least once across any of the platform's 15 formulations and 3 runs. 'Median formulation recall' reflects the median single-formulation recall across the 15 formulations — the metric representing a typical user query. 'Gap' = pooled recall minus median formulation recall, quantifying evidence within each platform's reach that is unlikely to surface from a typical formulation. Precision and consistency medians are across 15 formulations. Ai2 Finder's pooled recall significantly exceeded ChatGPT-4.1, Claude-Sonnet-4.0, and Gemini-2.5-Pro (all Bonferroni $p < 0.005$); its advantage over Consensus was not significant after correction ($p = 0.008$). At the formulation level (Friedman followed by pairwise Wilcoxon signed-rank with Benjamini–Hochberg correction), Ai2 Finder significantly outperformed all four other platforms (all $q \leq 0.0003$) and Consensus significantly outperformed Gemini-2.5-Pro ($q = 0.025$); no other pairwise comparison was significant.

QUERY-STRATEGY EFFECT ON RECALL (KRUSKAL–WALLIS)

Recall across the five prompting strategies (independent groups) was compared using the Kruskal–Wallis test on the 75 platform–formulation observations (5 platforms $\times$ 15 formulations), with FDR-corrected pairwise follow-up. Kruskal–Wallis $H(4) = 8.293$, $p = 0.0814$, $\eta^2 = 0.061$; 0 of 10 pairwise comparisons were significant after Benjamini–Hochberg FDR correction. A platform-blocked Friedman test on the same data gives $\chi^2 = 5.600$, $df = 4$, $p = 0.231$, Kendall's $W = 0.28$

Table S10. Median formulation-level recall by prompting strategy.

Strategy	Median recall	IQR	n
Zero-Shot	16.9%	[7.8%, 27.1%]	15
Few-Shot	13.3%	[7.2%, 27.7%]	15
Persona-based	13.3%	[9.0%, 18.7%]	15
Chain-of-Thought	4.8%	[3.6%, 20.5%]	15
PICO Framework	15.7%	[11.4%, 27.7%]	15

Notes. η^2 = eta-squared effect size. Values are pooled across the five platforms (75 observations). IQR = interquartile range. Values are medians across the 15 platform $\times$ variation formulations per strategy.

STRATEGY-LEVEL PERFORMANCE

Table S11. Strategy-level performance summary across all platforms (n=15 combinations per strategy: 5 platforms × 3 formulations).

Strategy	Recall mean (SD)	Recall range	Precision mean (SD)	F1 mean (SD)	F1 range	Top F1 configuration
Zero-Shot	0.199 (0.148)	0.048–0.506	0.231 (0.158)	0.154 (0.068)	0.055–0.306	Gemini V2 (F1 = 0.306)
Few-Shot	0.193 (0.145)	0.060–0.446	0.219 (0.173)	0.174 (0.109)	0.055–0.381	ChatGPT V2 (F1 = 0.381)
Persona-based	0.169 (0.137)	0.012–0.458	0.195 (0.146)	0.145 (0.073)	0.011–0.252	Claude V1 (F1 = 0.252)
Chain-of-Thought	0.113 (0.100)	0.024–0.277	0.266 (0.124)	0.122 (0.077)	0.040–0.251	Ai2 Finder V2 (F1 = 0.251)
PICO Framework	0.222 (0.135)	0.084–0.494	0.141 (0.051)	0.155 (0.053)	0.092–0.264	Ai2 Finder V1 (F1 = 0.264)

Notes. Summary statistics were computed across the 15 platform–formulation combinations within each strategy (5 platforms × 3 formulations). ‘Top F1 configuration’ identifies the single highest-F1 cell within the strategy.

PART 4. Prompting Framework

This Supplementary Content documents the complete specifications of the 15 prompt formulations evaluated across five RAG-LLM platforms.

Terminology: A *variation* (V0, V1, or V2) is one version within a prompting strategy. A *formulation* is one complete prompt created by pairing a strategy with a variation (e.g., Zero-Shot V0). The 15 formulations represent all 5 strategies × 3 variations.

The framework integrates three complementary sources: (1) established prompting strategies from the NLP and prompt engineering literature (zero-shot, few-shot, persona-based, chain-of-thought); (2) adapted practices from medical information retrieval and healthcare systematic review methodology, including MeSH-based terminology hierarchies, clinically current substance-use vocabulary (person-first language, disorder-focused terminology), and contrastive example construction; and (3) the PICO clinical evidence synthesis structure, adapted as a domain-specific retrieval framework. This integration is designed to test prompting approaches that clinicians and researchers would plausibly construct in real evidence-seeking practice — prioritizing ecological validity over orthogonal single-factor isolation.

The PICO strategy represents a **domain-specific structural adaptation** from evidence-based medicine applied to RAG-LLM retrieval evaluation, not an established prompting strategy from the NLP literature. It examines whether clinical question structure benefits LLM-based retrieval and how constraint positioning within this framework affects retrieval scope.

Complete verbatim prompts are provided in **Table S14** to enable exact replication. **Tables S12 and S13** document design principles and core concepts. **Table S15** documents concurrent modifications to support transparent interpretation.

Table S12. Formulation design principles

Design Principle	Source	Application in This Study	Formulations
Literature-Informed Strategies	Prompt engineering and NLP literature	Five strategies with documented effectiveness: zero-shot (direct specification), few-shot (example-based demonstration), persona-based (role assignment), chain-of-thought (explicit reasoning), and PICO framework (clinical evidence structure adapted for retrieval)	All 15 formulations
Domain-Practice Adaptation	Medical information retrieval; healthcare systematic review practice	MeSH-based hierarchical terminology; clinically current substance-use vocabulary ("substance use disorders" vs. "substance abuse"; person-first language); contrastive example construction; role specification as systematic reviewer; constraint positioning	Zero-Shot V1–V2; Few-Shot V0; Persona V1; Chain-of-Thought V0–V2; PICO V0–V2
Exploratory Hypotheses	Novel design questions without direct precedent in retrieval literature	Positive-only vs. contrastive example effectiveness; mission statement benefits beyond domain expertise; discourse-inclusive verb effects ("discussed" vs. "employed"); constraint positioning across input, source, and output levels within PICO structure	Few-Shot V1–V2; Persona V2; PICO V0–V2
Ecological Validity Priority	Real-world query construction in systematic review and clinical evidence-seeking contexts	Formulations resemble queries researchers would plausibly construct rather than orthogonally varying single factors. Concurrent modifications reflect how researchers naturally combine elements when refining searches.	All 15 formulations (design philosophy)

Notes. PICO framework represents a domain-specific structural adaptation from evidence-based medicine applied to literature search, not an established prompting strategy. All 15 formulations prioritize ecological validity. Design principles are not mutually exclusive; most formulations reflect more than one principle.

Table S13. Core concepts explored by prompting strategy and variation

Strategy	Research Question	V0 Concept	V1 Concept	V2 Concept	Literature Basis
Zero-Shot Prompting	How does substance specification approach affect retrieval breadth and consistency?	Enumerated list specification: 9 specific substance names with strict mandatory filters	Hierarchical taxonomy specification: general + specific categories with scope-expanding language (MeSH-inspired)	Clinical phenotyping terminology: disorder-focused language ("SUD", "electronic phenotyping") emphasizing validation	Medical IR practices (Clark 2014; Aromataris 2014); Clinical terminology evolution (Botticelli & Koh 2016; Kelly et al. 2016)
Few-Shot Prompting	How does example composition affect retrieval performance and precision?	Contrastive examples: 3 relevant + 4 irrelevant studies with explicit boundary labels	Positive-only examples: 5 relevant studies; irrelevant examples	Discourse-inclusive examples: relaxed verb ("employed"→"discussed");	Contrastive learning theory (Chen et al. 2020; Gao et al. 2021); In-context learning (Min et al. 2022; Liu et al. 2022; Brown et al. 2020)

Strategy	Research Question	V0 Concept	V1 Concept	V2 Concept	Literature Basis
			removed; universal quantifiers added	6 examples including conference proceeding	
Persona-Based Prompting	How does identity specification affect retrieval comprehensiveness?	Generic identity: "You are a Researcher." — minimal role without domain or methodological specification	Domain expertise identity: health informatics researcher conducting a systematic review	Mission-driven identity: domain expert with explicit healthcare policy and practice application goals	Role prompting literature (White et al. 2023; Salewski et al. 2024; Shanahan et al. 2023)
Chain-of-Thought Prompting	How does task verb choice affect retrieval consistency when reasoning structure is held constant?	"Provide" verb: delivery-oriented framing; identical 4-stage reasoning arc (Identify→Extract→Format→Generate)	"Locate" verb: discovery-oriented framing; identical 4-stage reasoning arc	"Identify" verb: classification-oriented framing with focus specification; identical 4-stage reasoning arc	Instruction framing effects (Reynolds & McDonell 2021; Efrat & Levy 2020); CoT framework (Wei et al. 2022; Kojima et al. 2022)
PICO Framework Prompting†	How does constraint positioning within a clinical evidence structure affect retrieval scope?	Input-level constraint: quantity threshold in opening query statement ("Retrieve at least 100 papers")	Source-level expansion: threshold removed; database scope maximized ("from all available databases")	Output-level constraint: threshold repositioned to format specification ("format with at least 100 studies")	Clinical evidence framework (Richardson et al. 1995; Hosseini et al. 2024); Query formulation (Guan 2025)

Notes. †PICO framework is a domain-specific structural adaptation from evidence-based medicine, not an established prompting strategy from the NLP literature. Variation labels (V0, V1, V2) reflect the primary concept explored; concurrent modifications are documented in Table S15.

Table S14. Verbatim prompt texts with design rationale

Note. Prompts are reproduced verbatim to enable exact replication. 'Core Concept Explored' names the primary design variable for each variation. 'Key Design Features' lists structural and linguistic elements operationalizing the concept. 'Concurrent Modifications' documents additional changes introduced alongside the primary concept. Few-shot example studies embedded in Few-Shot and Persona formulations were excluded from recall calculations in all analyses.

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
Zero-Shot	V0	Enumerated substance specification	Execute a comprehensive search for studies using NLP on clinical records to identify mentions of specific substances. The search should explicitly include terms for: alcohol, opioids, heroin, fentanyl, cocaine, cannabis, marijuana, methamphetamines, and benzodiazepines. STRICT FILTERS: The study must be a full paper published in a peer-reviewed journal or on a reputable preprint server. The data source must be clinical text from an EHR. Performance metrics such as precision, recall, and F1-score must be reported. For each of	• Explicit list of 9 substance names with mandatory inclusion • Labeled constraint section: "STRICT FILTERS" • Structured 5-component output template • Quantified result range: 50–100 studies	Baseline formulation — no prior variation. <i>Literature basis:</i> Medical IR practice (Clark 2014; Aromataris 2014)

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
			the 50-100 most relevant results, detail the following: 1. Full citation and link. 2. Substances the model was trained to detect. 3. Type of NLP approach. 4. The achieved performance metrics. 5. A concise note on its contribution.		
Zero-Shot	V1	Hierarchical taxonomy specification	TASK: Synthesize the state of research on the use of Natural Language Processing (NLP), text mining, or information extraction to analyze unstructured EHR data, clinical notes, progress notes, or discharge summaries. The goal is to find studies that detect, classify, predict, or phenotype any form of substance use. SEARCH SCOPE: The search should be highly inclusive, covering all substance-related terms such as: General: substance use, drug misuse, substance abuse, addiction, dependence, overdose, polysubstance use. Specifics: alcohol, opioids (heroin, fentanyl), stimulants (cocaine, methamphetamines), cannabis (marijuana, THC), benzodiazepines, and other non-prescribed or misused medications. INCLUSION CRITERIA: Find 50-100 full-text, peer-reviewed research papers or methodologically sound preprints. The studies must report quantitative performance metrics (e.g., F1-score, precision, recall, AUC) for their models. Exclude reviews, abstracts, and studies focused on social media or survey data. OUTPUT FORMAT FOR EACH STUDY: 1. Citation: Full citation with a clickable DOI link. 2. Substances Detected: List the specific substances or conditions (e.g., Opioid Use Disorder). 3. NLP Approach: Categorize the method (e.g., Rule-based, Machine Learning, Transformer). 4. Key Performance Metrics: Report the primary metrics achieved. 5. Contribution Note: A concise summary of the study's relevance or key finding.	- Multi-section structure: TASK / SEARCH SCOPE / INCLUSION CRITERIA / OUTPUT FORMAT - Hierarchical terms: general categories + specific examples - Scope-expanding language: "any form", "all substance-related terms", "highly inclusive" - Method diversification: NLP / text mining / information extraction	Multi-section architecture, method specification broadening, and exclusion criteria introduced alongside hierarchical terminology. <i>Literature basis:</i> MeSH-based hierarchical organization (Clark 2014; Aromataris 2014)
Zero-Shot	V2	Clinical phenotyping terminology	Identify and synthesize research studies on electronic phenotyping or automated cohort identification for substance use disorders (SUD) using NLP applied to unstructured EHR clinical notes (e.g., progress notes, discharge summaries). Focus on original algorithm development and validation. INCLUSION CRITERIA: Full-length, peer-reviewed publications or reputable preprints. Model development using unstructured clinical text (not surveys or structured codes only). Performance metrics reported: PPV/Precision,	- Clinical informatics framing: "electronic phenotyping", "automated cohort identification" - Disorder-focused terminology: "substance use disorders", "SUD phenotype" (vs. "substance abuse") - Validation	Task focus shifted from mention detection to clinical phenotyping; metrics prioritization and validation requirements emphasized simultaneously. <i>Literature basis:</i> Person-first clinical language; clinical informatics

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
			Sensitivity/Recall, F1-score, AUC, etc. Any SUD phenotype (e.g., opioid use disorder, alcohol use disorder, cannabis use, benzodiazepine misuse). OUTPUT FORMAT FOR EACH STUDY (repeatable across 50–100 results): 1. Citation (with clickable DOI link). 2. Target Phenotype: Substance use disorder diagnosed or identified (e.g., Opioid Use Disorder, Alcohol Misuse). 3. NLP Technique: Rule-based, traditional ML, deep learning, transformer-based, hybrid, QA, prompt-based, etc. 4. Key Performance Metrics: Emphasis on PPV/Precision and Sensitivity/Recall (plus F1-score, AUC). 5. Relevance Note: 1–2 sentence summary of algorithm contribution and validation context.	requirement: "original algorithm development and validation" • Clinical metrics prioritization: PPV/Precision, Sensitivity/Recall	terminology (Botticelli & Koh 2016; Kelly et al. 2016)
Few-Shot	V0	Contrastive example composition	Search the web to provide a reference list of all studies that employed natural language processing to identify substance use in unstructured clinical notes. Examples of Relevant Studies: 1. Afshar M, Dligach D, Sharma B, et al. Development and Application of a High Throughput Natural Language Processing Architecture to Convert All Clinical Documents in a Clinical Data Warehouse into Standardized Medical Vocabularies. <i>J Am Med Inform Assoc.</i> 2019;26(11):1364-1369. Focus: Opioid misuse detection. 2. Tavabi N, Swartz J, Oviatt S, et al. Characterizing Documentation of Cannabis Use Across a Large Health System Using Natural Language Processing. <i>npj Digital Medicine.</i> 2023;6:123. Focus: Cannabis use documentation. 3. Wicentowski R, Sydes MR. Using Implicit Information to Identify Smoking Status in Smoke-Blind Medical Discharge Summaries. <i>J Am Med Inform Assoc.</i> 2008;15(1):29-31. Focus: Smoking status identification. Examples of Irrelevant Studies: 1. Systematic review of fibromyalgia treatments - published in <i>Medicina-Lithuania</i> . 2. Hepatitis C virus infection classification using laboratory results - published in <i>Gastrointestinal Disorders</i> . 3. Machine learning for colorectal neoplasia prediction using colonoscopy reports - published in <i>PLOS ONE</i> . 4. Predicting COPD readmission risk using structured EHR data - published in <i>Information Systems Frontiers</i> . Provide only list of titles for the studies you retrieved.	• Dual example categories with explicit labels • Relevant examples (n=3) with full bibliographic citations • Irrelevant examples (n=4) with topic + journal descriptions • Domain contrast in negatives: fibromyalgia, HCV, colorectal neoplasia, COPD	Baseline few-shot formulation. <i>Literature basis:</i> Contrastive learning theory (Chen et al. 2020; Gao et al. 2021)

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
Few-Shot	V1	Positive-only examples with universal scope	Search the web to provide a reference list of all studies that employed ANY natural language processing tool to identify ANY substance use in unstructured clinical notes. Examples of Relevant Studies: 1. Afshar M, Dligach D, Sharma B, et al. Development and Application of a High Throughput Natural Language Processing Architecture to Convert All Clinical Documents in a Clinical Data Warehouse into Standardized Medical Vocabularies. JMIR Med Inform. 2023. Focus: Opioid misuse detection. 2. Tavabi N, Swartz J, Oviatt S, et al. Characterizing Documentation of Cannabis Use Across a Large Health System Using Natural Language Processing. npj Digital Medicine. 2023. Focus: Cannabis use documentation. 3. Gabriel RA, Sharma BS, Doan CN, et al. A Predictive Model for Determining Patients Not Requiring Prolonged Hospital Length of Stay After Elective Primary Total Hip Arthroplasty. Anesthesia and Analgesia. 2019. Focus: Persistent opioid use prediction. 4. Lingeman JM, Wang P, Becker WC, et al. Interactive Machine Learning for Opioid Misuse Detection From Primary Care Notes. AMIA Annual Symposium Proceedings. 2017. Focus: Opioid-related aberrant behavior identification. 5. Wicentowski R, Sydes MR. Using Implicit Information to Identify Smoking Status in Smoke-Blind Medical Discharge Summaries. J Am Med Inform Assoc. 2008. Focus: Smoking status identification. Provide only list of titles for the studies you retrieved.	• Single example category: relevant only (n=5) • All irrelevant examples removed • Universal quantifiers: "ANY natural language processing tool...ANY substance use" • Expanded venue diversity: 5 publications across JMIR, npj, Anesthesia & Analgesia, AMIA, JAMIA	Example structure changed from contrastive to positive-only AND scope expanded via universal quantifiers simultaneously. <i>Literature basis</i> : In-context learning (Min et al. 2022; Liu et al. 2022; Brown et al. 2020)
Few-Shot	V2	Discourse-inclusive verb with expanded example set	Search the web to provide a reference list of all studies that discussed ANY natural language processing tool to identify ANY substance use in unstructured clinical notes. Examples of Relevant Studies: 1. Afshar M, et al. JMIR Med Inform. 2023. Focus: Opioid misuse detection. 2. Tavabi N, et al. npj Digital Medicine. 2023. Focus: Cannabis use documentation. 3. Gabriel RA, et al. Anesthesia and Analgesia. 2019. Focus: Persistent opioid use prediction. 4. Lingeman JM, et al. AMIA Annual Symposium Proceedings. 2017. Focus: Opioid-related aberrant behavior identification. 5. Wicentowski R, Sydes MR. J Am Med Inform Assoc. 2008. Focus: Smoking status identification. 6. Alzoubi H, Taha Z, Alzboon A, et al. Detecting Alcohol Use Status From EHR Using Machine	• Verb relaxation: "employed" (implementation) → "discussed" (discourse) • Extended example set (n=6) with conference proceeding added (IEEE iCCECE) • Abbreviated citation format: author, journal, year, focus • Universal quantifiers maintained	Verb changed AND example set extended with conference proceeding simultaneously. <i>Literature basis</i> : Instruction framing effects; in-context learning (Min et al. 2022; Liu et al. 2022)

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
			Learning. International Conference on Computer and Electrical Engineering (iCCECE). 2018. Focus: Alcohol use status detection. Provide only list of titles for the studies you retrieved.		
Persona-Based	V0	Generic identity — minimal role framing	You are a Researcher. Search the web to provide a reference list of all studies that employed natural language processing to identify substance use in unstructured clinical notes. Provide only list of titles for the studies you retrieved.	• Single-sentence role declaration: "You are a Researcher." • No domain specialization, no methodological framing • Minimal three-line structure: Role → Task → Output • Baseline for persona strategy comparisons	Baseline persona formulation. <i>Literature basis:</i> Role prompting literature (White et al. 2023; Shanahan et al. 2023)
Persona-Based	V1	Domain expertise identity with methodological context	You are a health informatics researcher conducting a systematic review. Search the web to provide a reference list of all studies that employed ANY natural language processing tool to identify ANY substance use in unstructured clinical notes. Provide only list of titles for the studies you retrieved.	• Two-component role: "health informatics researcher conducting a systematic review" • Domain specification: health informatics • Methodological framing: systematic review context • Universal quantifiers: "ANY tool...ANY substance"	Identity specification AND universal quantifiers introduced simultaneously. <i>Literature basis:</i> Role prompting — domain-specific identity effects (Salewski et al. 2024; Shanahan et al. 2023)
Persona-Based	V2	Mission-driven identity with policy application purpose	You are a health informatics researcher conducting a systematic review to synthesize current evidence relevant to healthcare policy and practice. Search the web to provide a reference list of all studies that employed ANY natural language processing tool to identify ANY substance use in unstructured clinical notes. Provide only list of titles for the studies you retrieved.	• Three-component role: domain + methodology + mission • Mission statement: "to synthesize current evidence relevant to healthcare policy and practice" • Temporal emphasis: "current" evidence • Applied relevance framing: policy and practice orientation	Mission statement and temporal framing added to V1 identity structure. <i>Literature basis:</i> Role prompting — progressive identity elaboration (White et al. 2023; Salewski et al. 2024)

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
Chain-of-Thought	V0	"Provide" verb — delivery-oriented task framing	Your task is to provide studies related to the use of NLP in detecting substance use within clinical notes. Before you generate the final output, follow these steps carefully: 1. Identify Studies: Search your knowledge for academic papers specifically about using Natural Language Processing (NLP) to find evidence of substance use within clinical notes or electronic health records. 2. Extract Data: For each study you find, extract three pieces of information: the full Title, the Author(s), and the Journal of publication. 3. Format Output: Structure your final answer in tab-separated value (TSV) format. The very first line must be a header row containing these exact words separated by tabs: Title\Author\Journal. Each subsequent line must contain the information for a single study, with the title, author(s), and journal separated by tabs. If a piece of information for a study is not available, use the text [Not Available] in its place. 4. Generate Response: Provide only the final, TSV-formatted text as your answer. Do not include any introductory text or explanation.	• Pre-output directive: "Before you generate the final output, follow these steps carefully:" • 4-stage reasoning arc: Identify → Extract → Format → Generate • Task verb: "provide" studies • TSV output format with structured header row • Missing data protocol: [Not Available]	Baseline CoT formulation. All V0–V2 share identical 4-stage reasoning; only opening task verb varies. <i>Literature basis</i> : Instruction framing (Reynolds & McDonell 2021); CoT framework (Wei et al. 2022; Kojima et al. 2022)
Chain-of-Thought	V1	"Locate" verb — discovery-oriented task framing	Your task is to locate research studies on the application of NLP methods for identifying substance use within clinical notes. Before you generate the final output, follow these steps carefully: 1. Identify Studies: Search your knowledge for academic papers specifically about using Natural Language Processing (NLP) to find evidence of substance use within clinical notes or electronic health records. 2. Extract Data: For each study you find, extract three pieces of information: the full Title, the Author(s), and the Journal of publication. 3. Format Output: Structure your final answer in tab-separated value (TSV) format. The very first line must be a header row containing these exact words separated by tabs: Title\Author\Journal. Each subsequent line must contain the information for a single study, with the title, author(s), and journal separated by tabs. If a piece of information for a study is not available, use the text [Not Available] in its place. 4. Generate Response: Provide only the final, TSV-formatted text as your answer. Do not include any introductory text or explanation.	• Task verb: "locate" research studies • Discovery-oriented framing • Application emphasis: "application of NLP methods for identifying" • Identical 4-stage reasoning arc as V0	Verb only — all other elements identical to V0. <i>Literature basis</i> : Instruction framing effects (Reynolds & McDonell 2021; He et al. 2024)

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
Chain-of-Thought	V2	"Identify" verb — classification-oriented task framing	Your task is to identify research studies focused on the use of NLP methods to detect substance use within clinical notes. Before you generate the final output, follow these steps carefully: 1. Identify Studies: Search your knowledge for academic papers specifically about using Natural Language Processing (NLP) to find evidence of substance use within clinical notes or electronic health records. 2. Extract Data: For each study you find, extract three pieces of information: the full Title, the Author(s), and the Journal of publication. 3. Format Output: Structure your final answer in tab-separated value (TSV) format. The very first line must be a header row containing these exact words separated by tabs: Title\Author\Journal. Each subsequent line must contain the information for a single study, with the title, author(s), and journal separated by tabs. If a piece of information for a study is not available, use the text [Not Available] in its place. 4. Generate Response: Provide only the final, TSV-formatted text as your answer. Do not include any introductory text or explanation.	• Task verb: "identify" research studies • Classification-oriented framing • Focus specification: "focused on the use of NLP methods" • Purpose alignment: "to detect" substance use • Identical 4-stage reasoning arc as V0 and V1	Verb and focus specification only — all other elements identical to V0 and V1. <i>Literature basis:</i> Instruction framing effects (Efrat & Levy 2020; Reynolds & McDonell 2021)
PICO Framework†	V0	Input-level constraint — quantity threshold at task specification	Retrieve at least 100 papers that meet this PICO framework outline in identifying papers that employ NLP to detect substance use from electronic health records. P (Population/Problem): patients whose clinical information is represented in clinical texts (EHR, EMR, clinical notes, discharge summaries) from 2000 to present. I (Intervention): patients who use substances such as alcohol, opioids, cannabis, cocaine, amphetamines, methamphetamine, benzodiazepines, tobacco, polysubstance, or illicit drugs. C (Comparison): Not applicable. O (Outcome): Identification or screening of substance abuse, misuse, addiction, or substance-related disorders. Note: Study must apply any natural language processing (NLP) method (rule-based, machine learning, deep learning models such as BERT, or large language/transformer-based models) for analyzing clinical texts. Include studies published from 2000 to the present. Studies should report performance metrics such as precision, recall, F1-score, or AUC. Produce output in a table format with title, author, DOI, etc.	• PICO structure with 4 labeled components (P/I/C/O) • C component explicitly stated as "Not applicable" • Quantity threshold in opening statement: "Retrieve at least 100 papers" • Task verb: "Retrieve" • 4 NLP method types enumerated; temporal scope: 2000–present (stated twice) • Table output format	Baseline PICO formulation. <i>Literature basis:</i> PICO clinical evidence framework (Richardson et al. 1995; Hosseini et al. 2024); query formulation research (Guan 2025)

Strategy	Var.	Core Concept Explored	Verbatim Prompt Text	Key Design Features	Concurrent Modifications & Rationale
PICO Framework†	V1	Source-level expansion — threshold removed, database scope maximized	Give me all papers that meet this PICO framework outline in identifying papers that employ NLP to detect substance use from electronic health records from all available databases. P (Population/Problem): patients whose clinical information is represented in clinical texts (EHR, EMR, clinical notes, discharge summaries) from 2000 to present. I (Intervention): patients who use substances such as alcohol, opioids, cannabis, cocaine, amphetamines, methamphetamine, benzodiazepines, tobacco, polysubstance, or illicit drugs. C (Comparison): Not applicable. O (Outcome): Identification or screening of substance abuse, misuse, addiction, or substance-related disorders. Note: Study must apply any natural language processing (NLP) method (rule-based, machine learning, deep learning models such as BERT, or large language/transformer-based models) for analyzing clinical texts. Include studies published from 2000 to the present. Studies should report performance metrics such as, but not limited to, precision, recall, F1-score, or AUC. Produce output in a table format with title, author, DOI, etc.	- Quantity threshold removed from opening - Universal quantifier: "Give me all papers" - Database scope expansion: "from all available databases" - Task verb changed: "Give me" (replaced "Retrieve") - Metric flexibility added: "such as, but not limited to" - Identical PICO structure (P/I/C/O) as V0	Constraint removal, verb change, source expansion, and metric flexibility introduced simultaneously. <i>Literature basis:</i> PICO framework; query breadth effects (Bates 1989; Marchionini 2006)
PICO Framework†	V2	Output-level constraint — quantity threshold repositioned to format specification	Produce all papers that meet this PICO framework outline in identifying papers that employ NLP to detect substance use from electronic health records. P (Population/Problem): patients whose clinical information is represented in clinical texts (EHR, EMR, clinical notes, discharge summaries) from 2000 to present. I (Intervention): patients who use substances such as alcohol, opioids, cannabis, cocaine, amphetamines, methamphetamine, benzodiazepines, tobacco, polysubstance, or illicit drugs. C (Comparison): Not applicable. O (Outcome): Identification or screening of substance abuse, misuse, addiction, or substance-related disorders. Note: Study must apply any natural language processing (NLP) method (rule-based, machine learning, deep learning models such as BERT, or large language/transformer-based models) for analyzing clinical texts. Include studies published from 2000 to the present. Studies should report performance metrics such as precision, recall, F1-score, or AUC. Produce output in a table format with at least 100 studies, including title, author, DOI, etc.	- Quantity threshold repositioned to output specification: "format with at least 100 studies" - Task verb: "Produce" (replaced "Give me") - Opening statement: "Produce all papers" (universal quantifier retained) - Metric flexibility removed: standard list restored - Identical PICO structure as V0 and V1	Threshold repositioning, verb change, and metric specification standardization introduced simultaneously. <i>Literature basis:</i> Constraint positioning effects (Guan 2025; Bates 1989)

Notes. Prompts are provided verbatim. Formulations designed to resemble realistic user queries rather than tightly controlled single-factor manipulations. Where multiple elements vary between formulations (see Table S15), observed performance differences cannot be attributed to any single change. Few-shot example studies were excluded from recall calculations. †PICO = Population/Intervention/Comparison/Outcome framework adapted from evidence-based medicine.

Many formulations introduce their primary concept alongside additional modifications. This reflects realistic query construction, where researchers naturally combine changes when refining a search (e.g., adopting clinical terminology while reorganizing prompt structure). The table below documents all concurrent changes to enable transparent interpretation of observed retrieval patterns. Observed performance differences should not be interpreted as isolable effects of single elements.

Table S15. Concurrent modifications and interpretation framework

Transition	Primary Concept Explored	Concurrent Modifications Introduced	Interpretation Note
Zero-Shot V0→V1	Hierarchical taxonomy vs. enumerated specification	Organizational structure (single-flow → multi-section); method specification broadening (NLP → NLP/text mining/information extraction); exclusion criteria added; action verb expanded (identify → detect/classify/predict/phenotype)	Performance differences may reflect hierarchical terminology, organizational clarity, method breadth, exclusion filtering, or combinations thereof
Zero-Shot V1→V2	Clinical phenotyping terminology vs. general technical terminology	Task focus shifted (general detection → clinical phenotyping application); metrics prioritization changed (standard → PPV/Sensitivity emphasis); validation requirements made explicit; data restrictions added (excludes surveys/structured codes)	Performance differences may reflect clinical terminology adoption, application focus shift, metrics prioritization, validation emphasis, or combinations thereof
Few-Shot V0→V1	Positive-only examples vs. contrastive example structure	Example structure changed (contrastive → positive-only); example count changed (3 relevant → 5 relevant; 4 irrelevant → 0); scope expanded via universal quantifiers ("ANY tool...ANY substance")	Performance differences may reflect example structure modification, scope expansion, example quantity change, or combinations thereof
Few-Shot V1→V2	Discourse-inclusive verb vs. implementation-focused verb	Task verb relaxed ("employed" → "discussed"); example set extended (5 → 6, adding conference proceeding); citation format abbreviated (full → author/journal/year/focus)	Performance differences may reflect verb relaxation, additional example provision, venue diversification, or combinations thereof
Persona V0→V1	Domain expertise identity vs. generic researcher identity	Identity specification added (health informatics); methodological framing added (systematic review); universal quantifiers introduced ("ANY tool...ANY substance")	Performance differences may reflect domain expertise specification, systematic review framing, scope expansion, or combinations thereof
Persona V1→V2	Mission-driven identity vs. expertise identity alone	Mission statement added ("synthesize current evidence relevant to healthcare policy and practice"); temporal emphasis made explicit ("current" evidence); applied relevance framing added	Performance differences may reflect mission statement presence, temporal framing, applied relevance emphasis, or combinations thereof
PICO V0→V1	Source-level expansion vs. input-level constraint	Quantity threshold removed from opening; task verb changed ("Retrieve" → "Give me"); database scope expanded ("from all available databases"); metric flexibility introduced ("but not limited to")	Performance differences may reflect threshold removal, verb modification, database scope expansion, metric flexibility, or combinations thereof
PICO V1→V2	Output-level constraint vs. source-level expansion	Quantity threshold repositioned to output specification ("format with at least 100 studies"); task verb changed ("Give me" → "Produce"); metric specification standardized (flexibility removed)	Performance differences may reflect constraint repositioning, verb change to production framing, metric standardization, or combinations thereof

Notes. Each row describes changes between adjacent variations within a strategy. 'Primary Concept Explored' names the intended design variable; 'Concurrent Modifications' lists all additional changes introduced alongside it. Because these formulations prioritize ecological validity over single-factor isolation, performance patterns characterize retrieval under concept-driven combinations rather than establishing causal effects of individual elements.

PART 5. Cross-Platform Coverage and Complementarity

Table S16. Unique and shared study contributions by platform (aggregated across all formulations and runs).

Platform	Total retrieved (pooled)	Pooled recall %	Shared with ≥ 1 other platform	Unique to this platform	Unique study identifiers
Ai2 Finder	60	72.3%	50	10 (16.7%)	Caccamisi 2020, Keyhani 2018, Manca 2021, Miranda 2024, Muizelaar 2024, Palmer 2019a, Regan 2016, Wang 2018, Wu 2013, Yu 2021
Consensus	44	53.0%	43	1 (2.3%)	Alba 2024
Gemini-2.5-Pro	42	50.6%	41	1 (2.4%)	Roosan 2024
ChatGPT-4.1	43	51.8%	43	0 (0.0%)	None
Claude-Sonnet-4.0	38	45.8%	36	2 (5.3%)	Harris 2020, Turchin 2023

Notes. 'Total retrieved' = unique gold-standard studies retrieved by the platform across all 15 formulations and 3 runs. 'Unique to this platform' = gold-standard studies retrieved by this platform and no other platform across any condition.

Table S17. Greedy sequential combination strategy (n=225 experimental conditions; 83-study gold standard).

Step	Platform	Strategy	Variation	New studies added	Cumulative total	Cumulative coverage	Marginal gain
1	Ai2 Finder	Zero-Shot	V1	44	44	53.0%	100.0% (baseline)
2	Consensus	Zero-Shot	V1	13	57	68.7%	22.8% relative increase
3	Claude-Sonnet-4.0	Few-Shot	V2	5	62	74.7%	8.1%
4	Ai2 Finder	Few-Shot	V0	3	65	78.3%	4.6%
5	Ai2 Finder	PICO	V0	2	67	80.7%	3.0%
6	Consensus	PICO	V0	1	68	81.9%	1.5%
7	Claude-Sonnet-4.0	PICO	V2	1	69	83.1%	1.5%
8	Gemini-2.5-Pro	PICO	V2	1	70	84.3%	1.4%
9	Consensus	Zero-Shot	V2	1	71	85.5%	1.4%
10	Ai2 Finder	PICO	V2	1	72	86.7%	1.4%
11	Consensus	Few-Shot	V0	1	73	88.0%	1.4%

Notes. Each step adds one platform–formulation configuration selected by a greedy algorithm to maximize marginal coverage increase of the 83-study gold standard. 'New studies added' indicates unique gold-standard studies contributed beyond those already covered by previously selected configurations. Cumulative coverage reflects union recall after each addition. Analysis was executed on the University of Florida HiperGator high-performance computing cluster across all 2,775 possible pairwise combinations.

Table S18. All 10 pairwise platform combinations ranked by union recall.

Rank	Platform pair	Combined coverage (n)	Combined coverage (%)	Shared by both	Unique to first	Unique to second	Jaccard similarity	Complementarity score
1	Ai2 Finder + Claude-Sonnet-4.0	69	83.1%	29	31	9	0.420	0.580
2	Ai2 Finder + Consensus	68	81.9%	36	24	8	0.529	0.471
3	Ai2 Finder + Gemini-2.5-Pro	68	81.9%	34	26	8	0.500	0.500
4	Ai2 Finder + ChatGPT-4.1	66	79.5%	37	23	6	0.561	0.439
5	Consensus + ChatGPT-4.1	59	71.1%	28	16	15	0.475	0.525
6	Consensus + Claude-Sonnet-4.0	58	69.9%	24	20	14	0.414	0.586
7	Consensus + Gemini-2.5-Pro	57	68.7%	29	15	13	0.509	0.491
8	ChatGPT-4.1 + Gemini-2.5-Pro	52	62.7%	33	10	9	0.635	0.365
9	ChatGPT-4.1 + Claude-Sonnet-4.0	50	60.2%	31	12	7	0.620	0.380
10	Claude-Sonnet-4.0 + Gemini-2.5-Pro	49	59.0%	31	7	11	0.633	0.367

Notes. Combined coverage = union of gold-standard studies retrieved by both platforms across all their formulations and runs. Jaccard similarity = $\text{Both} / (\text{Both} + \text{Unique1} + \text{Unique2})$. Complementarity score = $1 - \text{Jaccard similarity}$. All 2,775 possible pairwise combinations from 75 platform–formulation configurations were evaluated.

PART 6. Retrieval Patterns by Evidence Domain and Publication Characteristics

The following tables report the probability of zero retrieval per formulation — the proportion of the 15 formulations returning no gold-standard studies for a given evidence domain — and the complementary probability of retrieving at least one relevant study per query. Platform differences were tested using Cochran's Q applied to the binary zero-retrieval outcome per formulation (15 matched blocks). The domains analysed in this section were pre-specified (substance categories and venue type).

Table S19. Single-query zero-retrieval probability per platform, by evidence domain.

Evidence domain (n; % of corpus)	Ai2 Finder	Consensus	ChatGPT-4.1	Claude-Sonnet-4.0	Gemini-2.5-Pro	Cochran's Q	p-value
Tobacco (28; 33.7%)	47%	60%	80%	67%	73%	9.87	0.043 *
Opioids (20; 24.1%)	33%	33%	40%	33%	40%	3.00	0.558

Evidence domain (n; % of corpus)	Ai2 Finder	Consensus	ChatGPT-4.1	Claude-Sonnet-4.0	Gemini-2.5-Pro	Cochran's Q	p-value
Alcohol (10; 12.0%)	33%	53%	67%	67%	67%	8.35	0.080
Cannabinoids (4; 4.8%) †	33%	53%	80%	80%	60%	12.89	0.012 *
Polysubstance (17; 20.5%)	33%	33%	33%	33%	40%	4.00	0.406
Other (4; 4.8%) †	40%	60%	60%	47%	67%	4.50	0.343
Conference proceedings (18; 21.7%)	33%	53%	73%	67%	67%	9.12	0.058
Pre-2016 (8; 9.6%)	53%	100%	87%	87%	87%	16.00	0.003 *

Notes. Values are the single-query zero-retrieval probability for each platform: the proportion of the 15 query formulations (each pooled across 3 runs) that returned no gold-standard study from that domain. Platforms were compared within each domain using Cochran's Q (df = 4) on the binary per-formulation zero-retrieval outcome (15 matched blocks); two-tailed, $\alpha = 0.05$. * overall Cochran's Q significant at $\alpha = 0.05$ (tobacco, cannabinoids). Where the overall test was significant, post-hoc McNemar pairwise comparisons with Bonferroni correction ($\alpha = 0.005$ across 10 comparisons per domain) were applied; no pairwise comparison reached significance after correction in any domain (closest: Ai2 vs ChatGPT-4.1 and Ai2 vs Claude-Sonnet-4.0 for cannabinoids, $p = 0.016$ uncorrected). † $n = 4$; the estimate is imprecise. Substance categories are mutually exclusive and sum to 83; conference proceedings is a venue-type domain ($n = 18$) and Pre-2016 a publication-period domain ($n = 8$). * Overall Cochran's Q significant at $\alpha = 0.05$ (tobacco, cannabinoids, Pre-2016).

PUBLISHER AND VENUE ANALYSIS

Table S20. Publisher-level retrieval analysis (ordered by retrieval tier).

Publisher	Studies (n)	Overall retrieval rate	Never-retrieved (n)	Ai2 Finder	Consensus	ChatGPT	Claude	Gemini	All 5
Oxford (OUP)	15	100%	0	14 (93%)	11 (73%)	10 (67%)	6 (40%)	6 (40%)	4
MDPI	5	100%	0	5 (100%)	2 (40%)	3 (60%)	2 (40%)	3 (60%)	1
PLOS	4	100%	0	4 (100%)	1 (25%)	0 (0%)	1 (25%)	1 (25%)	0
Wiley	4	100%	0	4 (100%)	1 (25%)	4 (100%)	3 (75%)	3 (75%)	1
IOS Press	3	100%	0	2 (67%)	3 (100%)	1 (33%)	2 (67%)	2 (67%)	1
JMIR	3	100%	0	3 (100%)	3 (100%)	3 (100%)	3 (100%)	3 (100%)	3
SAGE	2	100%	0	2 (100%)	2 (100%)	1 (50%)	0 (0%)	1 (50%)	0
Taylor & Francis	2	100%	0	2 (100%)	1 (50%)	1 (50%)	0 (0%)	1 (50%)	0
ASCO	1	100%	0	0 (0%)	1 (100%)	1 (100%)	0 (0%)	0 (0%)	0
BMJ	1	100%	0	1 (100%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	0
Frontiers	1	100%	0	1 (100%)	1 (100%)	1 (100%)	1 (100%)	1 (100%)	1
SciTePress	1	100%	0	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0
Taylor & Francis (Dove)	1	100%	0	1 (100%)	0 (0%)	1 (100%)	1 (100%)	1 (100%)	0
Wolters Kluwer	1	100%	0	0 (0%)	1 (100%)	1 (100%)	1 (100%)	1 (100%)	0
Elsevier	11	91%	1	6 (55%)	8 (73%)	4 (36%)	7 (64%)	6 (55%)	3

Publisher	Studies (n)	Overall retrieval rate	Never-retrieved (n)	Ai2 Finder	Consensus	ChatGPT	Claude	Gemini	All 5
Springer Nature	10	90%	1	9 (90%)	3 (30%)	6 (60%)	5 (50%)	4 (40%)	0
AMIA	5	80%	1	1 (20%)	1 (20%)	2 (40%)	3 (60%)	2 (40%)	0
ACL	3	67%	1	2 (67%)	1 (33%)	1 (33%)	1 (33%)	2 (67%)	1
Thieme	2	50%	1	1 (50%)	1 (50%)	0 (0%)	0 (0%)	1 (50%)	0
IEEE	7	43%	4	2 (29%)	2 (29%)	3 (43%)	2 (29%)	3 (43%)	0
ACM	1	0%	1	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0
TOTAL	83	—	10	—	—	—	—	—	15

Notes. Overall retrieval rate = proportion of a publisher's studies retrieved by ≥ 1 platform under any condition; Never-retrieved (n) = studies retrieved by no platform; platform columns = number (%) of the publisher's studies retrieved by that platform (≥ 1 of its 15 formulations); All 5 = studies retrieved by all five platforms. Publisher–non-retrieval associations were not significant (Benjamini–Hochberg FDR-adjusted $p > 0.05$).

CONTENT DOMAIN AND TEMPORAL ANALYSIS

Table S21. Platform-level retrieval by substance domain.

Substance domain	Studies (n)	% of corpus	Ai2 Finder	Consensus	ChatGPT	Claude	Gemini	Mean retrieval %
Opioids	20	24.1%	16 (80%)	16 (80%)	14 (70%)	11 (55%)	12 (60%)	69.0%
Alcohol	10	12.0%	9 (90%)	5 (50%)	6 (60%)	6 (60%)	6 (60%)	64.0%
Cannabinoids	4	4.8%	4 (100%)	2 (50%)	3 (75%)	2 (50%)	3 (75%)	70.0%
Tobacco	28	33.7%	15 (54%)	5 (18%)	10 (36%)	10 (36%)	7 (25%)	33.6%
Polysubstance / multiple	17	20.5%	14 (82%)	13 (76%)	8 (47%)	7 (41%)	11 (65%)	62.4%
Other	4	4.8%	2 (50%)	3 (75%)	2 (50%)	2 (50%)	3 (75%)	60.0%

Notes. Platform-specific values = number (%) of studies in that substance domain retrieved by each platform, aggregated across all formulations and runs. Substance-domain stratification is descriptive; formal significance testing for platform differences within each domain was conducted using the zero-retrieval probability metric.

Table S22. Retrieval by NLP methodology.

NLP methodology	Studies (n)	% of corpus	Ai2 Finder	Consensus	ChatGPT	Claude	Gemini	Mean %
Rule-based	44	53.0%	31 (70%)	24 (55%)	23 (52%)	19 (43%)	21 (48%)	53.6%
Conventional machine learning	15	18.1%	12 (80%)	5 (33%)	9 (60%)	9 (60%)	9 (60%)	58.7%
Deep learning (non-transformer)	9	10.8%	7 (78%)	7 (78%)	5 (56%)	4 (44%)	4 (44%)	60.0%

NLP methodology	Studies (n)	% of corpus	Ai2 Finder	Consensus	ChatGPT	Claude	Gemini	Mean %
Large language models	15	18.1%	10 (67%)	8 (53%)	6 (40%)	6 (40%)	8 (53%)	50.7%

Notes. Methodology categories reflect the primary NLP approach as classified in the gold standard. Platform-specific values aggregate across all formulations and runs. ChatGPT-4.1 and Claude-Sonnet-4.0 showed the lowest retrieval of LLM-based studies (both 40%) in this corpus. Methodological retrieval rates are descriptive.

Table S23. Retrieval by publication year.

Year range	Studies (n)	Overall retrieval ≥ 1 platform	Ai2 Finder	Consensus	ChatGPT	Claude	Gemini	None
2006–2010	5	60%	2 (40%)	0 (0%)	3 (60%)	2 (40%)	1 (20%)	40%
2011–2015	3	67%	2 (67%)	0 (0%)	0 (0%)	0 (0%)	1 (33%)	33%
2016–2018	11	82%	7 (64%)	4 (36%)	5 (45%)	4 (36%)	4 (36%)	18%
2019	9	100%	9 (100%)	5 (56%)	5 (56%)	5 (56%)	7 (78%)	0%
2020	8	75%	4 (50%)	4 (50%)	3 (38%)	4 (50%)	3 (38%)	25%
2021	9	100%	9 (100%)	5 (56%)	6 (67%)	5 (56%)	3 (33%)	0%
2022	10	80%	7 (70%)	7 (70%)	7 (70%)	3 (30%)	6 (60%)	20%
2023	15	93%	9 (60%)	11 (73%)	8 (53%)	9 (60%)	9 (60%)	7%
2024	13	100%	11 (85%)	8 (62%)	6 (46%)	6 (46%)	8 (62%)	0%

Notes. ‘Overall retrieval’ = proportion retrieved by at least one platform under any condition. ‘None’ = proportion not retrieved by any platform (universal misses). Per-platform cells are counts (and percentages) of that year-stratum’s studies retrieved by each platform. Consensus retrieved none of the 8 studies published before 2016 (2006–2015); the contrast with 2016-onward retrieval (44 of 75, 59%) is significant (Fisher's exact $p = 0.0016$). Some early strata have small n .

PUBLICATION-PERIOD TEMPORAL ANALYSIS

Temporal retrieval was analyzed primarily by individual publication year (Table S23, Part 6), with the Consensus pre-2016 gap summarized in that table’s footnote. Because single-year strata are too sparse for a platform comparison, studies were also grouped into calendar-defined decade bins for that test (Figure S2).

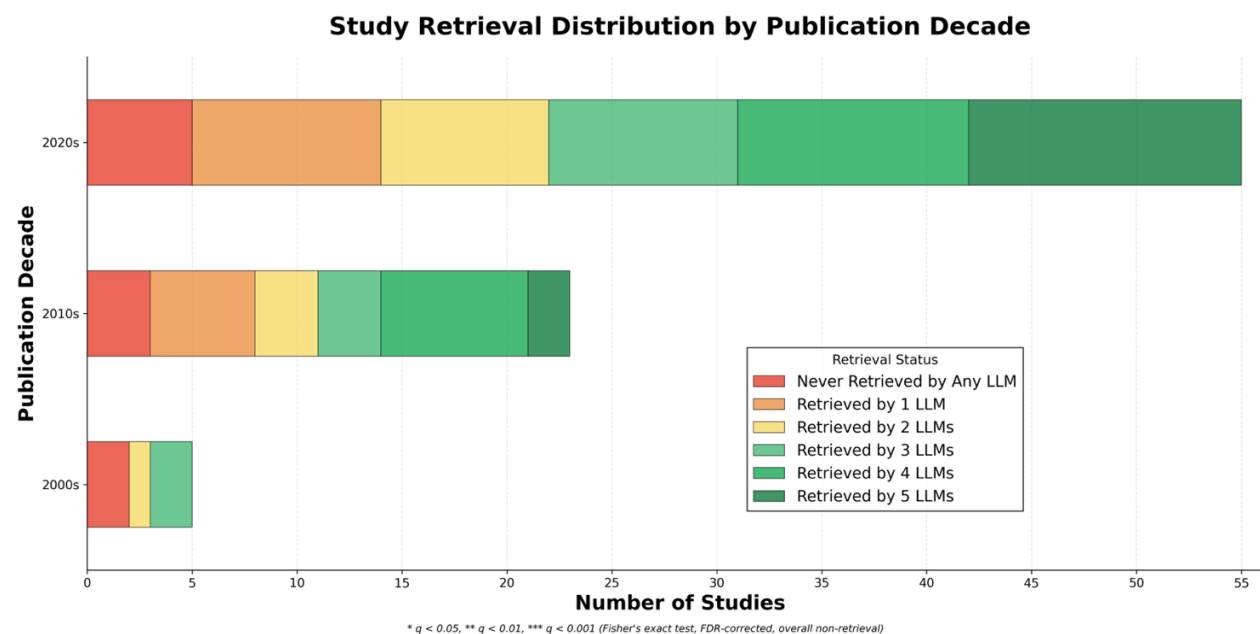


Figure S2. Study-level retrieval by publication period. Proportion of gold-standard studies retrieved at least once by each platform within each stratum. The primary analysis is by individual publication year (Table S23); decade bins (2000s, $n=5$; 2010s, $n=23$; 2020s, $n=55$) provide the platform comparison, which was significant in the 2010s (Cochran's $Q=13.62$, $p=0.009$) and 2020s ($Q=14.17$, $p=0.007$).

PART 7. Never-Retrieved and Difficult-to-Retrieve Studies

Table S24. Complete list of never-retrieved studies ($n=10$; not retrieved by any platform under any of the 225 experimental conditions).

Study	Year	Publisher	Venue type	Methodology	Substance domain
Zeng 2006	2006	Springer Nature	Journal	Rule-based	Tobacco
McCormick 2008	2008	AMIA	Conference	Rule-based	Tobacco
Figuerola 2014	2014	IEEE	Conference	Conventional ML	Tobacco
Mowery 2017	2017	ACL	Conference	Rule-based	Tobacco
Patel 2018	2018	Thieme	Journal	Conventional ML	Tobacco
Groenhof 2020	2020	Elsevier	Journal	Rule-based	Tobacco
Wang 2020	2020	IEEE	Conference	Rule-based	Opioids
Kugic 2022	2022	IEEE	Conference	LLM	Alcohol

Study	Year	Publisher	Venue type	Methodology	Substance domain
Patel 2022	2022	ACM	Conference	Rule-based	Tobacco
Bhate 2023	2023	IEEE	Conference	LLM	Polysubstance

Notes. Studies were classified as never-retrieved if not retrieved by any of the five platforms under any of the 15 formulations or 3 runs (n=225 total conditions). Venue type, methodology, and substance domain reflect the classifications used in the coverage pattern analysis.

Table S25. Convergent characteristics of never-retrieved studies (n=10) compared with gold-standard distribution.

Characteristic	Never-retrieved (n=10)	% of never-retrieved	% of gold standard (n=83)
Conference proceedings	7	70.0%	21.7%
IEEE publisher	4	40.0%	8.4%
Tobacco substance domain	7	70.0%	33.7%
Rule-based methodology	6	60.0%	53.0%
Published before 2016	3	30.0%	9.6%

Notes. Percentages for never-retrieved studies are relative to the 10-study never-retrieved set. Gold-standard percentages are relative to all 83 studies.

PLATFORM-SPECIFIC NON-RETRIEVAL ANALYSIS

This section details, for each platform, which gold-standard studies were never retrieved (across all 15 formulations and 3 runs), how those missed studies were distributed with respect to retrieval by other platforms, and which studies represent platform-specific blind spots not shared by other platforms. All counts reflect pooled platform-level retrieval.

Table S26. Platform-specific non-retrieval summary: total missed studies and distribution by cross-platform retrieval status.

Platform	Never-retrieved (n; %)	Retrieved by 0 others (universal misses)	Retrieved by 1 other only	Retrieved by 2 others	Retrieved by 3 others	Retrieved by 4 others (unique failures)
Ai2 Finder	23 (27.7%)	10 (43.5%)	4 (17.4%)	3 (13.0%)	3 (13.0%)	3 (13.0%)
Consensus	39 (47.0%)	10 (25.6%)	13 (33.3%)	3 (7.7%)	5 (12.8%)	8 (20.5%)
ChatGPT-4.1	40 (48.2%)	10 (25.0%)	14 (35.0%)	9 (22.5%)	5 (12.5%)	2 (5.0%)
Claude-Sonnet-4.0	45 (54.2%)	10 (22.2%)	12 (26.7%)	11 (24.4%)	8 (17.8%)	4 (8.9%)
Gemini-2.5-Pro	41 (49.4%)	10 (24.4%)	13 (31.7%)	10 (24.4%)	7 (17.1%)	1 (2.4%)

Notes. ‘Never-retrieved’ = not retrieved across any of the 15 formulations or 3 runs for that platform. ‘Retrieved by 0 others’ = universal misses (not retrieved by any platform). ‘Retrieved by 4 others’ = platform-specific unique failure (all other four platforms retrieved it).

Table S27. Platform-specific unique failures: gold-standard studies retrieved by all four other platforms but not by the listed platform.

Platform	n	Study identifiers	Shared characteristics of unique failures
Ai2 Finder	3	Lybarger 2018, Yang 2020, Gabriel 2023	Conference proceedings (2/3); AMIA and IEEE venues; 2018–2023 publication range
Consensus	8	Alzoubi 2018, Bae 2021, Palmer 2019b, Ebrahimi 2024, Arribas 2024, Tavabi 2023, McDermott 2023, Hazlehurst 2019	All journal articles (not conference proceedings); mixed publishers (Springer, Wiley, Oxford, PLOS); 2018–2024; Consensus-specific blind spot not shared by any other platform
ChatGPT-4.1	2	Topaz 2019, Afshar 2019	Both 2019; IOS Press and PLOS; opioid and tobacco focus
Claude-Sonnet-4.0	4	Badger 2019, Kim 2023, Alzubi 2022, Carrell 2022	2019–2023; mixed publishers (Elsevier, IEEE, MDPI, Taylor & Francis)
Gemini-2.5-Pro	1	Sharma 2020	Springer Nature; 2020; only platform-specific unique failure for Gemini

Notes. Unique failures are studies retrieved by all four other platforms (aggregated across formulations and runs) but not by the listed platform. Consensus has the most unique failures (n=8), all journal articles; Ai2 Finder’s unique failures (n=3) are predominantly conference proceedings. Platform-specific non-retrieval associations were assessed using Fisher’s exact tests with FDR correction (Section A1.3.4).

Table S28. Complete list of never-retrieved studies by platform.

Platform	Never-retrieved studies (Author Year; aggregated across all formulations and runs)
Ai2 Finder	Mowery 2017, Patel 2022, McCormick 2008, Lingeman 2017, Lybarger 2018, Harris 2020, Ruckdeschel 2023, Turchin 2023, Kashyap 2023, Liu 2023, Groenhof 2020, Yusuf 2022, Figueroa 2014, Wang 2020, Yang 2020, Kugic 2022, Bhate 2023, Alba 2024, Wicentowski 2008, Roosan 2024, Zeng 2006, Patel 2018, Gabriel 2023
Consensus	Jonnagaddala 2015, Mowery 2017, Patel 2022, McCormick 2008, Lingeman 2017, Harris 2020, Yu 2021, Turchin 2023, Wang 2018, Groenhof 2020, Figueroa 2014, Alzoubi 2018, Wang 2020, Kugic 2022, Bhate 2023, Bae 2021, Manca 2021, Miranda 2024, deBoer 2022, Wicentowski 2008, Savova 2008, Clark 2008, Wu 2013, Regan 2016, Keyhani 2018, Roosan 2024, Zeng 2006, Palmer 2019a, Palmer 2019b, Muizelaar 2024, Ebrahimi 2024, Arribas 2024, Tavabi 2023, Caccamisi 2020, McDermott 2023, Patel 2018, Lin 2022, Hazlehurst 2019, Green 2019

ChatGPT-4.1	Jonnagaddala 2015, Mowery 2017, Patel 2022, McCormick 2008, Harris 2020, Yu 2021, Seng 2024, Turchin 2023, Schirle 2021, Kashyap 2023, Liu 2023, Wang 2018, Groenhof 2020, Yusuf 2022, Figueroa 2014, Wang 2020, Kugic 2022, Bhate 2023, Topaz 2019, Alba 2024, Manca 2021, Miranda 2024, Soysal 2018, Dligach 2019, Lybarger 2023, Richie 2023, Petit-Jean 2024, Wu 2013, Regan 2016, Keyhani 2018, Afshar 2019, Hutto 2024, Roosan 2024, Zeng 2006, Palmer 2019a, Roy 2024, Muizelaar 2024, Caccamisi 2020, Feller 2020, Patel 2018
Claude-Sonnet-4.0	Jonnagaddala 2015, Mowery 2017, Patel 2022, McCormick 2008, Yu 2021, Ruckdeschel 2023, Seng 2024, Wang 2018, Badger 2019, Groenhof 2020, Yusuf 2022, Figueroa 2014, Wang 2020, Kugic 2022, Bhate 2023, Kim 2023, Alba 2024, Manca 2021, Miranda 2024, Alzubi 2022, deBoer 2022, Clark 2008, Soysal 2018, Dligach 2019, Thompson 2021, Lybarger 2023, Richie 2023, Petit-Jean 2024, Haller 2017, Wu 2013, Regan 2016, Keyhani 2018, Zhu 2022, Hutto 2024, Roosan 2024, Afshar 2021, Zeng 2006, Palmer 2019a, Roy 2024, Muizelaar 2024, Carrell 2022, Caccamisi 2020, Feller 2020, Patel 2018, Green 2019
Gemini-2.5-Pro	Mowery 2017, Patel 2022, McCormick 2008, Harris 2020, Yu 2021, Ruckdeschel 2023, Seng 2024, Turchin 2023, Schirle 2021, Liu 2023, Wang 2018, Groenhof 2020, Figueroa 2014, Wang 2020, Kugic 2022, Bhate 2023, Alba 2024, Manca 2021, Miranda 2024, deBoer 2022, Savova 2008, Clark 2008, Soysal 2018, Dligach 2019, Thompson 2021, Richie 2023, Petit-Jean 2024, Haller 2017, Wu 2013, Regan 2016, Keyhani 2018, Zhu 2022, Afshar 2021, Zeng 2006, Palmer 2019a, Sharma 2020, Roy 2024, Muizelaar 2024, Caccamisi 2020, Patel 2018, Lin 2022

Notes. Studies listed as Author Year. All studies in this table were not retrieved by the listed platform across any of the 15 prompt formulations or 3 independent runs. Studies appearing in all five platform lists are the 10 universal misses (Table S24). The 10 universal misses appear in every row. Studies appearing in only one platform's list are that platform's unique failures (Table S27).

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