



SCRAPPOINT · WHITE PAPER

From LinkedIn Search to a Scalable B2B Data Pipeline

The end-to-end architecture: collection, normalization, QA, storage, export, and refresh — stage by stage.

For operations directors & data teams

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01

Executive Summary

The problem. Most agencies treat LinkedIn as a search box, not a data source. A researcher types filters, scrolls results, opens each profile, copies fields into a spreadsheet, formats them, and hands off a list. It works for one campaign. It does not work as a system. The moment volume rises, the same manual steps that produced the first thousand records become the thing that caps the next hundred thousand.

Why it matters. The cost of this model is hidden inside headcount. Sales and research staff spend roughly 37–40% of their time — about 16 hours a week — on account and prospect research rather than the work they were hired for [1]. Reps spend only around 40% of their time actively selling [2]. For an agency, that research time is the cost of goods sold, and it scales linearly with volume: to double output you roughly double the people.

The shift. A pipeline replaces a sequence of manual tasks with a set of stages that each have a defined input, a defined output, an owner, and a failure mode. Searching is not collecting. Collecting is not normalizing. Normalizing is not QA. When each stage is explicit, you can measure it, automate the repetitive parts, and keep humans on the judgment the machine cannot do.

Key findings.

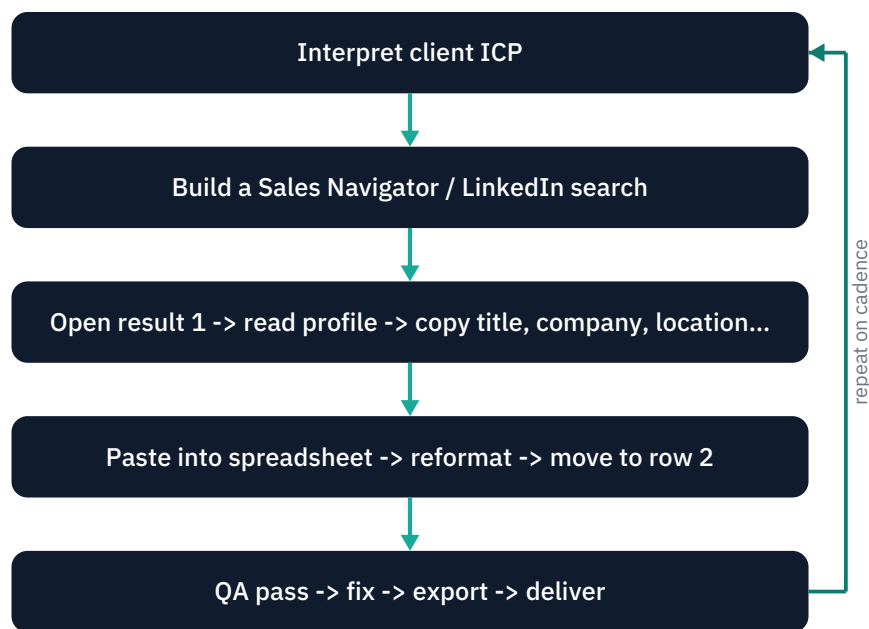
1. The bottleneck is almost never "finding" prospects — it is everything that happens after the search: extraction, standardization, dedupe, QA, storage, and refresh.
2. Data quality degrades at both ends: on the way in (inconsistent manual entry, duplicates) and over time (decay at ~2.1% per month) [3].
3. Up to 80% of new records entering a CRM through integrations are duplicates [4]; deduplication is a pipeline function, not a periodic cleanup.
4. Automation does not remove people. It moves them from copy-paste to ICP definition, exception handling, and client judgment.

Recommended approach. Design the eight-stage pipeline in this paper, decide the human-vs-automation split at each stage, and make collection, normalization, storage, and refresh infrastructure instead of tasks.

02

The Traditional LinkedIn Workflow

Almost every agency starts here, and most never leave. The workflow is a loop run by a person:



The defining feature of this workflow is that **output is a function of hours worked**. Ten researchers produce roughly twice what five produce. There is no leverage: nothing the team did last week makes this week faster, because the artifacts are disposable spreadsheets, not a growing asset.

It also hides its own cost. The research burden is distributed across many people doing "a 15–20 minute task" repeated thousands of times — a ten-person research team can lose roughly 148 of 400 available weekly hours to research alone [1]. No single step looks expensive. The sum is the operation.

03

Why the Traditional Workflow Breaks

The manual loop fails in predictable ways. They do not appear at low volume, which is exactly why they surprise agencies at high volume.

Failure point	What goes wrong	When it bites
Inconsistent entry	"VP, Marketing" vs "Vice President of Marketing" typed by hand	Immediately, invisibly

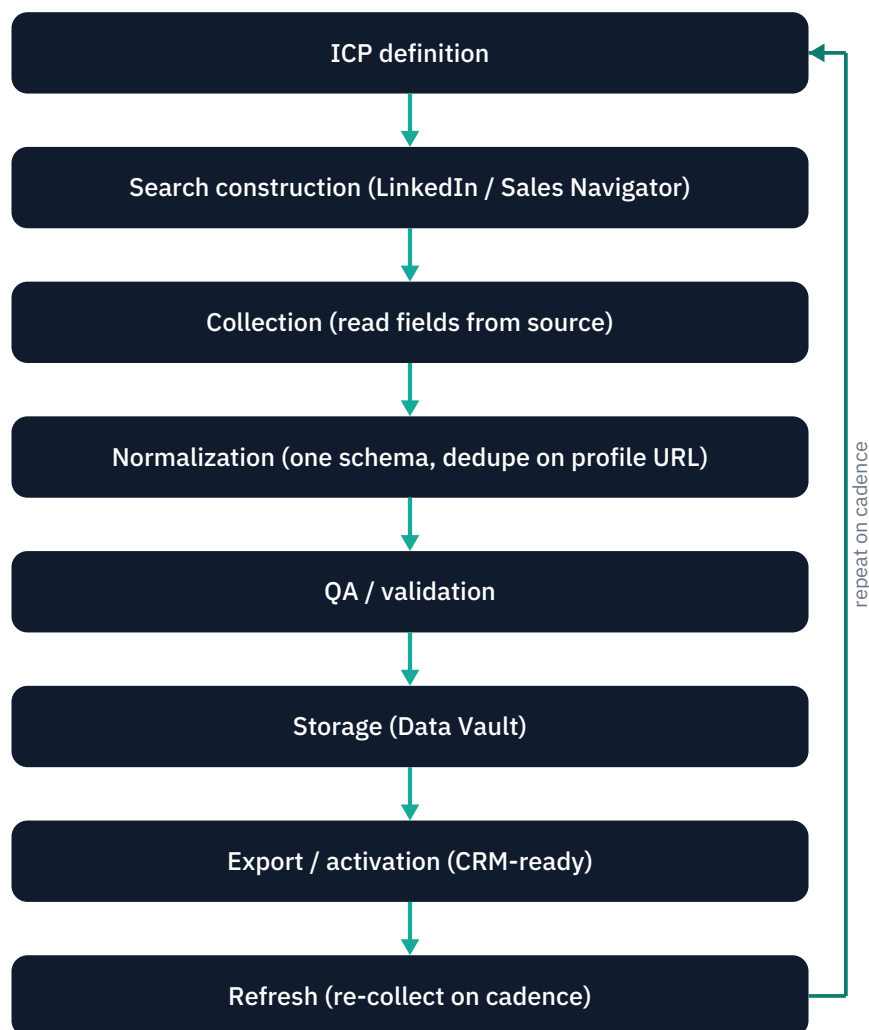
Failure point	What goes wrong	When it bites
Duplicates	Same person collected twice across searches / researchers	At multi-researcher scale
No system of record	Data lives in many files; no single source of truth	When lists must be reused
QA is human-on-human	A second person re-checks the first; same fatigue, same blind spots	Every batch
Rework	Errors found downstream trigger re-collection and re-delivery	After delivery, expensively
No refresh	Lists are one-time snapshots; decay is never addressed	~2.1%/month, compounding [3]
Format drift	Each researcher formats differently; exports don't match the CRM	On every handoff

Two numbers frame the damage. Only around 40% of selling time is spent selling [2], and data professionals routinely report spending the majority of their working time on data preparation and cleanup rather than analysis [5]. An agency running this workflow is paying skilled people to be a slow, error-prone ETL process.

The deeper issue: the manual workflow has **no place to put quality**. Freshness, consistency, and uniqueness are properties of a system. A pile of spreadsheets has nowhere to enforce them.

04 The Pipeline Architecture

A data pipeline reframes the same work as a series of stages. Each stage takes a defined input, does one job, and emits a defined output to the next stage. The agency stops asking "who is collecting this list?" and starts asking "is each stage healthy?"



The eight stages. ICP definition -> search construction -> collection -> normalization -> QA/validation -> storage -> export/activation -> refresh. Refresh is not a final step; it is a loop that feeds back into collection on a cadence.

Why stages matter. Each stage can be measured (records/hour, error rate, duplicate rate, freshness), owned (a person or a system), and improved independently. You can automate collection without touching how you define an ICP. You can tighten QA without re-architecting storage. The pipeline is what makes the operation diagnosable.

The division of labour that runs through the whole pipeline: **humans own definition and judgment; automation owns repetition and consistency.** The following pages take each stage in turn and name exactly where that line sits and what fails when it is drawn wrong.

05 The Collection Layer

Job: turn a search into structured records. This is the stage agencies most often confuse with the whole pipeline, and the stage where manual effort is most wasteful.

Input: a LinkedIn or Sales Navigator search URL (an ICP already expressed as filters). **Output:** one structured record per profile — name, headline/title, current company, location, and the other public fields the profile or search exposes — with the **LinkedIn profile URL captured as the primary key**.

Searching != collecting. A search returns a paginated list on screen. Collection is the act of reading each result into a durable, structured row. Doing that by hand is the 15–20-minute-per-prospect tax [1]; doing it as a pipeline stage makes it near-constant-cost per record.

Failure points at this layer:

- **Pagination limits.** Sales Navigator searches paginate automatically but

commonly surface up to roughly 2,500 results per search URL. Segments larger than that must be **sharded** into multiple searches (by geography, headcount band, industry) or records will silently be left uncollected.

- **Missing the key.** If the profile URL is not captured, you cannot dedupe or refresh later. The key is the most important field in the record.

- **Session and environment.** Collection should run under the customer's own

LinkedIn session and IP, in their own environment — not routed through a shared provider identity.

- **Over-collection.** Pulling fields LinkedIn does not expose, or inventing data, is not collection. The ceiling is "what the profile currently shows publicly."

Human vs automation. A human decides what to collect (which searches, which segments, when to shard). Automation does the collection itself — the reading and structuring that a person should never be doing by hand at volume.

06 The Normalization Layer

Job: make every record speak one language. Collection produces structured but inconsistent records; normalization enforces a single schema so the data is comparable, searchable, and CRM-ready.

Input: raw structured records from collection. **Output:** records conformed to one schema — consistent field names, consistent value formats, parsed and standardized titles, locations, and company references.

The consistency problem, concretely. The same role arrives three ways:

As collected / entered	Normalized value
VP Marketing	Vice President, Marketing

As collected / entered	Normalized value
Vice President of Marketing	Vice President, Marketing
VP, Marketing	Vice President, Marketing
V.P. — Marketing	Vice President, Marketing

To a human these are obviously the same person's role. To a database — and to any filter, segment, or dedupe routine — they are four different values. Without normalization, a search for "Vice President, Marketing" misses three of the four, and the client's segment is quietly wrong.

What normalization standardizes:

- **Titles** — a canonical form plus parsed seniority and function.
- **Locations** — consistent city / region / country structure.
- **Company references** — a stable company identity even when the displayed name

varies, so an unlinked text company and a linked company page reconcile.

- **Field names and types** — one schema, so every export maps cleanly to the CRM.

Failure point: normalization applied after data lands in many spreadsheets is a cleanup project that never finishes. Applied as a pipeline stage — on the way in, every time — it is a property of the dataset. This is the difference the research calls out: teams that try to clean at the end spend the majority of their time on preparation [5], while a normalization stage makes consistency automatic.

Human vs automation. Humans define the schema and the canonical forms (the rules). Automation applies them to every record, identically, forever.

07 The Quality Assurance / Validation Layer

Job: catch what is wrong or incomplete before it reaches storage and the client. In a manual shop, QA is one tired person re-reading another tired person's spreadsheet. In a pipeline, QA is a set of checks — some automated, some human — applied consistently.

Input: normalized records. **Output:** records that pass validation, plus a flagged-exceptions queue for human review.

Automated checks (the machine's job):

- **Completeness** — are the fields the client needs populated? Flag records

missing a title, company, or location.

- **Uniqueness** — is this profile URL already in the dataset? Deduplicate on the

key. This matters more than teams expect: up to 80% of records entering a CRM via integrations are duplicates [4], and well-run operations hold duplicates under 5% [6]. Dedupe is a continuous pipeline function, not a quarterly purge.

- **Validity** — is the profile URL well-formed and resolvable? Is a value in an impossible format?

- **Consistency** — did normalization actually produce canonical values?

Human review (the exception queue):

- Ambiguous ICP fit ("is a 'Growth Lead' in scope for a 'VP Marketing' campaign?").
- Edge cases the rules cannot adjudicate.
- Judgment calls the client has opinions about.

Why this split matters. Manual QA reduces error frequency without changing error type, because both the collector and the checker are human and share the same blind spots. Automated checks change the error type they catch entirely — they never get bored of comparing profile URLs. Humans are then spent only on the small fraction of records that genuinely need judgment. Target metrics worth tracking: under 5% duplicates, 80%+ field completion, and a bounce rate kept under 2% downstream [6][7].

08

The Storage Layer

Job: keep every collected record in one searchable system of record, so the dataset is an asset that grows rather than a drawer of disposable files.

Input: validated, normalized records. **Output:** a queryable, deduplicated store keyed on the profile URL.

Why storage is the stage spreadsheets cannot be. A spreadsheet is a file: one person edits it, versions fork, there is no shared key, and search is a manual scroll. As record counts cross 10,000 and then 50,000, the file is the failure — it cannot enforce uniqueness, cannot be queried, and cannot be the thing you refresh. (This is the subject of WP-03, The Spreadsheet Trap.) Storage replaces the file with a system that has:

- **A primary key** — the LinkedIn profile URL — so the same person is one row, not four, across every search and campaign they ever appeared in.
- **Searchability** — filter and segment the whole dataset, not one file at a time.
- **A single source of truth** — one place the data lives, versioned and owned,

rather than many copies drifting apart.

- **Dedupe at write time** — a record arriving for a key that already exists updates

that row instead of creating a second one.

Failure point: without a stable key at the storage layer, every later stage breaks. You cannot dedupe without it, you cannot refresh without it, and you cannot tell the client whether a name appears once or five times. The key chosen at collection (Page 6) is what makes storage work.

Human vs automation. This stage is almost entirely automation. The human decision is upstream — choosing the key and the schema — and from then on storage should be a system, not a person maintaining files.

09 The Data Vault

Job: be the specific storage system this pipeline targets — a searchable, deduplicated repository of every record the agency has ever collected, kept in one normalized schema.

This paper has described storage in the abstract; in a Scrapoint implementation the storage layer is the **Data Vault**. It is worth describing concretely because it is what turns "we ran some scrapes" into "we own a data asset."

What the Data Vault holds:

- Every collected profile and company record, in one normalized schema.
- Deduplicated on the LinkedIn profile URL — one person, one canonical row.
- Fully searchable, so any segment can be pulled without re-running a collection.

What it enables that a spreadsheet cannot:

Capability	Spreadsheet pile	Data Vault
Find a segment	Open files, scroll, hope	Query the whole dataset
One person = one row	Manual dedupe, never current	Keyed on profile URL, continuous
Reuse last quarter's work	Find the right file	It is already in the store
Refresh in place	Impossible at scale	Update the row for the key
Export to CRM	Reformat every time	Normalized schema maps cleanly

The Data Vault is the reason the pipeline compounds. Every collection adds to a growing, deduplicated, searchable asset instead of producing another disposable list. It is also the

precondition for refresh: you can only update in place what you are storing with a stable identity.

Boundary (stated plainly): the Data Vault holds the public LinkedIn and Sales Navigator fields that were collected — it does not contain personal emails or phone numbers, and it does not invent fields a profile never published.

10 The Export / Activation Layer

Job: get the right records out of the store and into the systems where work actually happens — the CRM, the campaign tool, the client's deliverable.

Input: a queried segment from the Data Vault. **Output:** a clean file or feed in the format the destination expects.

Formats and destinations:

- **CSV / JSON / Excel** exports for CRMs, outreach platforms, and client

handoffs; an API for programmatic pulls.

- Because records are already normalized to one schema, the export **maps cleanly**

to the destination's fields — no per-file reformatting, no researcher massaging columns before every handoff.

Activation is where data-quality debt comes due. This is the stage where stale or dirty data turns into a visible, external cost:

- Duplicates split activity history and cause two reps to contact the same person
- they surface at activation, after they have already done damage [4].
- Stale records drive bounces; practitioners keep bounce under 2%, and above ~4% it

burns sender reputation faster than warmup can repair, because inbox providers correlate bounces with low-quality sending [7]. One bad export degrades every future send from that domain.

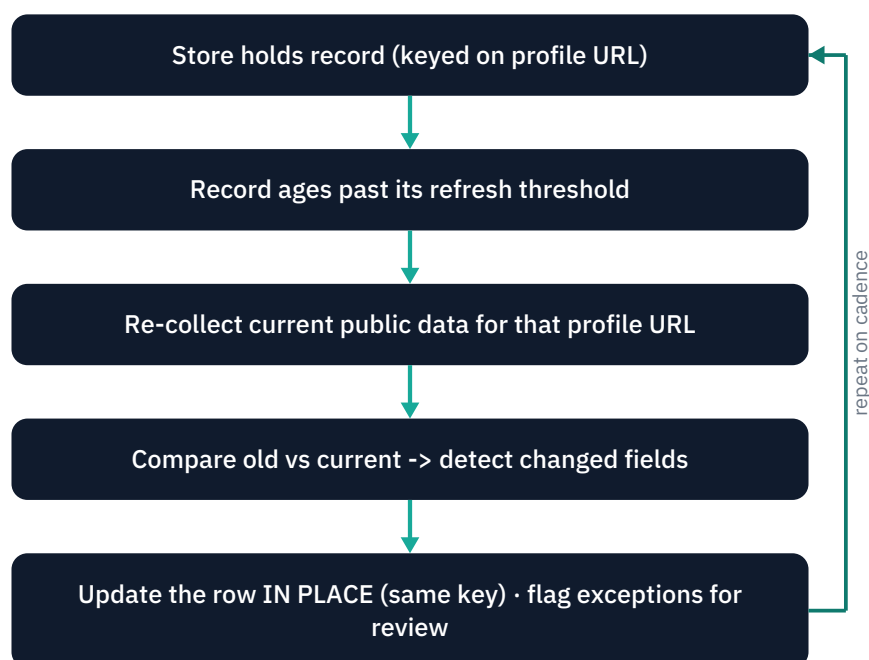
Human vs automation. The human decides which segment to activate and for what play. Automation produces the correctly-formatted output. The point of the upstream stages is that by the time data reaches activation, the human is choosing, not cleaning.

11 The Refresh Layer

Job: keep the stored dataset in sync with reality over time. This is the stage that separates a pipeline from a one-time scrape, and the one almost every manual operation omits entirely.

Why it is non-optional. B2B data decays at roughly 2.1% per month — about 22–30% a year at baseline, faster for volatile fields [3]. Job title is the fastest-decaying field, and it is the field agencies target on. Median US tenure is about 3.9 years and roughly a quarter of workers change jobs in a given year [8]. A dataset that is never refreshed is losing its most valuable, most-targeted records continuously.

How refresh works in the pipeline:



Prioritize by value x staleness rather than refreshing everything equally:

- High-value accounts — most often.
- Active-campaign contacts — before each campaign.
- Senior roles / fast-moving industries — shorter cycle (they decay faster).
- Older, lower-priority records — longer cycle.

The crucial mechanic — and its honest limit. Refresh works because records are keyed on the stable LinkedIn profile URL: re-collecting for that key updates the existing row instead of creating a duplicate. This means refresh is realistic only for records that carry that key in your store. It is not a magic wand that revives an arbitrary legacy database with no profile URLs — those records have to be matched to a profile URL first. Data cleaning is an event. Data freshness is a process.

Human vs automation. Humans set the cadence and the priorities. Automation runs the re-collection, the comparison, and the in-place update — the work no team can do by hand across 100,000 records.

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Build vs. Operate: A Capacity Model

The pipeline's value is a capacity you dial, not a headcount you hire. The difference shows up in how you add capacity, not just in cost.

Manual capacity = Analysts x Throughput per analyst
Pipeline capacity = Workers x Throughput per worker (scales by configuration)
Adding capacity: manual = recruit + onboard (weeks)
pipeline = add a worker (minutes)

Variable	Manual	Pipeline
Unit of capacity	A hired analyst	A configured worker
Lead time to add	Weeks (recruit, onboard)	Minutes (configuration)
Error type	Fatigue-driven, reducible	Transcription error removed at source
QA	Re-check every record	Spot-check the pipeline

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Worked Example: Serving 25,000 Records a Month

Illustrative — assumptions stated; not a measured result or a Scrapoint benchmark.

Model	To reach 25,000 records/month	To add more capacity
Manual	~8 analysts (~3,000 each) plus ~2 QA reviewers	Hire and onboard (weeks)
Pipeline	Queue the sharded searches across workers; QA is spot-checks	Add a worker (a configuration change)

The manual model's cost and lead time grow with every client. The pipeline's capacity is a dial — which is what lets volume rise without a hiring cycle in the critical path.

14 A 30 / 60 / 90-Day Rollout

Window	Focus	Key actions	Outcome
Days 0–30	Foundation	Stand up the store and one schema; define ICP searches	A system of record to build on
Days 31–60	Collection	Run source-level collection; normalize and dedupe on the profile URL	Clean, CRM-ready datasets
Days 61–90	Operate	Add export views and a refresh cadence; monitor per-stage health	A measured, scalable pipeline

15 Implementing the Pipeline with Scrapoint

Scrapoint is the **collection + normalization + storage + refresh layer** of this pipeline — stated strictly in terms of what it does:

Pipeline stage	What Scrapoint does (factually)
Collection	Collects public LinkedIn & Sales Navigator data — profiles, company pages, and lead/account searches — into structured records, under the customer's own session and IP
Normalization	Conforms every record to one schema ; standardizes fields for CRM-readiness
QA / dedupe	Deduplicates on the LinkedIn profile URL ; one person, one canonical row
Storage	Keeps records in a searchable Data Vault (single source of truth)
Export / activation	Exports CSV / JSON / Excel (and via API), mapped to a consistent schema
Refresh	Re-collects current public data keyed on the profile URL, updating rows in place

Where the human line sits in a Scrapoint implementation. The team defines the ICP and the searches, shards segments larger than ~2,500 results, sets the refresh cadence and priorities, and handles the exception queue and client judgment. Scrapoint owns the repetitive collection, the normalization, the dedupe, the storage, and the mechanical refresh.

What Scrapoint does not do (so the pipeline design is honest):

- It does not find or append personal **emails or phone numbers** — that is a different tool category; say so to clients rather than implying otherwise.
- It does not invent data a profile never published; collection keeps you in sync with what LinkedIn currently shows, no more.

Commercials, factually. Pricing is credit-based — one credit per delivered record — with a free tier of 1,000 credits, so an agency can run a real segment through the full pipeline before committing.

The result of implementing these stages is leverage: output stops being a linear function of headcount, because the repetitive work is infrastructure and the people are spent on definition, exceptions, and client outcomes.

16**Next Step**

If your researchers are still opening profiles and copying fields into spreadsheets, your agency is paying skilled people to be a slow ETL process — and paying again, every quarter, as that data decays. A pipeline changes the unit economics: collect, normalize, store, and refresh as infrastructure, and keep your people on judgment.

See how Scrapoint can own the collection, normalization, storage, and refresh layers of your prospect-data pipeline — so the search box becomes a system.

Book a demo · scrapoint.com/product · Start free with 1,000 credits

Sources

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