Pathzn: Turning Saved Inspiration into User-Controlled Action

Draft Capstone Paper

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Project Summary

Most people have a saved folder they never open. A recipe, a mobility routine, a two-minute explainer on starting seeds indoors: each one captured in a second, then buried under everything saved after it. Instagram and TikTok have made capture nearly effortless. What they have not built is anything that helps a person figure out which of those saves actually mattered, what acting on one would involve, or where to start.

Pathzn is a mobile application concept that works in that gap. Users share selected posts into a separate library, where AI writes a short summary, proposes a category, pulls out concrete details, and makes the item findable in ordinary language. When several saves seem to circle the same goal, the app can offer an editable Path: a handful of source-linked steps assembled from content the user already collected. The offer is exactly that, an offer. Nothing is built without a yes, and every generated line can be rewritten, reordered, or deleted.

The capstone deliverable is an interactive prototype and a research-based evaluation plan. It is not production software, and it does not involve training a model.

One principle runs through the whole project. Saving is not the problem; acting is. Success for Pathzn is not the number of Paths it generates. It is whether the few saves that genuinely mattered became easier to begin.

Problem Statement

People save constantly, and for good reason. Tapping the bookmark icon preserves an idea without derailing whatever else is happening. You keep scrolling, and the recipe is still there later. The trouble is asymmetry. Saving takes a second; returning takes intent. A collection that grows by five items a week and shrinks by none becomes, within a few months, something a person avoids opening. Platform folders help a little. They allow a user to name a collection and drop things into it. What they do not do is reduce the effort of remembering why an item is there, or of working out what using it would require.

I began this project treating that as a retrieval problem: too much saved, too hard to find. Secondary research pushed me somewhere less comfortable. A save may not be a failed attempt to act at all. It may be a small act of its own. Tapping the button registers the interest, closes the loop, and delivers a modest sense of having done something about it. What the save does not record is when the person meant to act, what the task actually requires, or which step comes first. The interest survives. The specifics do not.

That reframing changes what a good design would do. The obvious move, converting every save into a task, is the wrong one. People save to be entertained, to signal something about themselves, out of curiosity, for reference, and on the off chance. Turning all of it into commitments would manufacture the exact pressure Pathzn is supposed to relieve, and would trade a crowded folder for a crowded to-do list. The narrower and harder problem is to help users surface the small number of saves that carry real intention, and to make those specific enough to begin, while keeping organization light, AI behavior legible, and the decision to commit entirely in the user's hands.

Research Question and Objectives

The question driving the project is straightforward to state and difficult to answer: How might a digital tool help people revisit and act on saved inspirational or educational content without creating more organizational work?

Six questions sit underneath it.

- Why do people save, and what do they expect will happen afterward?

- What actually stops someone from returning to content they thought was worth keeping?
- What separates a casual save from a real intention, and can a user tell the difference in the moment or only in hindsight?
- Which kind of help matters most: search, summaries, resurfacing, extracted requirements, step-by-step plans, or some mix?
- When does an AI suggestion read as helpful rather than presumptuous?
- How much visibility and control do people expect over categories, summaries, groupings, and Paths the system produced on their behalf?

The objectives follow from those questions. Map how and why people save. Locate the point where interest stops turning into action. Build a prototype grounded in that evidence rather than in assumption. Test whether it improves clarity and confidence without adding work.

Approach and Conceptual Framework

This is a user-centered design project, which means Paths are a hypothesis rather than a conclusion. Research may show that people mostly need better search. It may show that a two-line summary solves most of the problem and that generated steps feel like homework. The work moves from secondary research to interviews, then synthesis, prototyping, testing, and revision, and the design should follow what participants say and do rather than what would be most interesting to build.

Four ideas frame the reasoning behind the design, and they form a chain. The literature review that follows examines the evidence behind each one. This section states how each is being used.

Keeping is cheaper than deciding. Digital-hoarding research explains why collections grow. Storage costs nothing, capture takes a second, and there is no penalty for one more item. I use this framework descriptively, not diagnostically. A full saved folder does not make someone a hoarder, and a saved tutorial can hold real value. What matters for design is that accumulation buries context. The more a person keeps without adding anything to it, the more work it takes to recover why it was kept.

Interest survives, specifics do not. Implementation intentions link a situation to a response, usually in if-then form (Gollwitzer, 1999). A save looks like a goal intention with the specifics stripped out. "I want to try this" says nothing about when, where, what is needed, or what comes first. Pathzn can supply that structure, but only after the user confirms the interest is worth acting on. The framework justifies planning after commitment. It does not justify treating every save as a commitment.

Specifics alone are not enough. The Fogg Behavior Model holds that behavior occurs when motivation, ability, and a prompt arrive together (Fogg, 2009). Saved content is a timing failure. At the moment of discovery there is motivation but no time, no ingredients, no equipment, no free evening. Weeks later the free evening exists and the motivation has evaporated, with nothing left to bring it back. This reframes the design question from "should Pathzn send reminders" to "can Pathzn lower the effort and appear when acting is actually possible."

Whatever the system does, the user has to be able to see it. AI can summarize, categorize, cluster, and draft steps, which removes most of the manual labor of organizing. Those savings are worth only what the user can verify. Research on trust in AI-enabled systems finds that trust is shaped by system qualities, design features, socio-ethical concerns, and the characteristics of the user (Bach et al., 2022). Transparency and correction therefore belong in the core interaction rather than in a settings screen. What came from the source stays distinguishable from what the model inferred, the original post stays one tap away, and anything the AI produced can be changed or discarded.

Literature Review

Saving Without Returning

Saving has become ordinary. A person can bookmark a TikTok recipe at lunch, an Instagram workout on the train, a career thread that evening, and an article before bed, and none of it interrupts anything. That is the appeal. The cost arrives later, when the collection is large enough that finding a specific item takes longer than searching for a new one. Pathzn starts from that gap. People are surrounded by information they deliberately kept, and the systems that helped them keep it offer almost nothing for what comes next.

No single body of literature studies saved social-media posts as a defined behavior. The problem falls between digital hoarding, personal information management, goal pursuit, persuasive design, and trust in artificial intelligence. Read together, these areas explain why saved content piles up and why tidier folders are unlikely to fix it. Read together, they also expose a gap. Accumulation and behavior change are studied apart from one another, and there is little guidance on moving saved content out of storage and into action the user actually chose.

Digital Hoarding and Accumulation

Sweeten, Sillence, and Neave (2018) define digital hoarding as accumulating digital material, struggling to delete it, and feeling anxious about the growing collection. Interviewing 45 adults, they found motivations that echo physical hoarding, above all the belief that something might be useful someday. Storage is cheap, saving is frictionless, and nothing bad happens when a person keeps one more thing. Deciding whether an item is worth keeping is harder than keeping it.

Neave, Briggs, McKellar, and Sillence (2019) developed a questionnaire to measure these behaviors and validated it with 424 adults, finding that accumulation and difficulty discarding hold together as consistent patterns. That work moves digital hoarding past a joke about a cluttered desktop and establishes it as behavior some people repeat across contexts.

The framework only carries Pathzn so far. A saved tutorial is not clutter, and most users with a crowded folder are not experiencing anything clinical. A save can be sincere interest or a genuine plan for later. The problem is less that things accumulate and more that accumulation makes their value hard to reach. Digital-hoarding research explains the pile. It should not be used to pathologize the person who made it.

That distinction has design consequences. A storage-management tool would push deletion. Pathzn keeps the content and works on the other side of the problem, making saved items understandable, findable, and, when the user wants, actionable.

From Intention to Action

The intention-action gap supplies a second lens. Gollwitzer (1999) argues that a strong goal intention does not reliably produce behavior, because a general intention leaves the beginning undefined. Implementation intentions remove that ambiguity by fixing a cue to a response. Not “I want to exercise,” but “if it is Monday at six, I go to the gym.”

Gollwitzer and Sheeran (2006) synthesized 94 independent studies and reported a medium-to-large effect of implementation intentions on goal attainment ($d = .65$). Follow-through improves when a person has named a cue and a response instead of waiting for motivation to reappear. A save is that intention with the naming left out. Bookmarking a meal-prep video may mean “I want to try this,” but it fixes no shopping trip, no ingredient list, and no first step.

The caveat matters as much as the finding. Not every save is a goal. People save to be entertained, to signal identity, to compare options, to look something up later, or for no reason they could articulate. Converting all of it into plans would turn Pathzn into a second inbox. Implementation-intention research supports structured planning after a goal has been chosen; nothing in it says every captured interest should become one. Which leaves the central design question: how does Pathzn tell, or ask, whether a save matters enough to act on?

This is also why Paths remain a hypothesis rather than a settled feature. Participants may want plans. They may equally report that decent search, a short summary, or a weekly resurfacing addresses most of the frustration and that generated steps feel like an assignment. The final emphasis should follow the evidence, not the most technically ambitious option.

Prompts, Ability, and Timing

Fogg (2009) offers a different explanation for failed follow-through: behavior occurs when motivation, ability, and a prompt converge at one moment. In saved-content behavior, the post supplies motivation, the motivation decays, and the post gets buried, so no prompt survives to reconnect the two. Even a well-timed reminder fails when ability is missing, and ability is often what is missing. The task is vague, or large, or expensive, or inconvenient.

That suggests resurfacing on its own will not accomplish much. A notification asking “Remember this video?” restores visibility and nothing else. A more useful system would summarize what the content actually contained, hold onto why it was kept, name what the task requires, and propose one step small enough to do. In Fogg’s terms, most of Pathzn’s contribution sits on the ability side rather than the prompt side.

Timing remains the risk. Prompts work when motivation and ability are both present and become noise otherwise. Some users may prefer a Sunday review to item-level pings. Others may want alerts only for content they flagged themselves. Frequency, context, and control are all things to test rather than assume.

AI Organization and User Trust

Artificial intelligence removes most of the manual labor in this space. It can generate summaries, identify topics, group related posts, extract requirements, and draft a sequence of steps. That capability fits the problem well, because tools requiring users to build their own folders, tags, and databases tend to get abandoned the same way platform collections were abandoned. If organizing inside Pathzn is work, the app fails on its own terms.

The labor savings are worth only what the user can verify. Bach et al. (2022) reviewed 23 empirical studies of trust in AI-enabled systems from an HCI perspective and found trust shaped by technical and design features, socio-ethical concerns, and user characteristics, while emphasizing user involvement throughout development and monitoring. That finding is directly relevant to an application that interprets someone’s interests and then makes suggestions about their life.

Trustworthy does not mean confident. Suggestions should stay visible and editable: open the source, fix a category, rewrite a summary, pull an item out of a cluster, reject a Path outright. The interface should also mark the boundary between extraction and inference. An ingredient stated in a video is not the same kind of claim as a model’s opinion about what to cook first.

The target is calibrated trust rather than maximum trust. Users should come away knowing what the system does well, where it is guessing, and how to correct it. A system that states wrong plans confidently loses trust and rarely gets it back. That puts source links, explanations, and correction controls in the prototype rather than in a future release.

The Gap

Each literature explains one piece. Hoarding research explains the pile. Implementation intentions explain what makes a chosen goal more likely to start. Fogg explains why motivation, ability, and prompt have to arrive at once. Trust research explains what an AI assistant owes the person using it.

Saved social content sits between information and intention, and the two are usually treated as separate problems. Some saves are idle. Others are the closest thing a person has to a plan. Platforms optimize for capture and, at best, retrieval; they do not help anyone decide what deserves attention, work out what it would take, or begin. There is also little guidance on when AI assistance reads as considerate rather than intrusive. Pathzn works in that gap, studying how people save and testing whether light organization plus optional planning can support follow-through without converting interests into obligations.

Research Methodology

The approach is user-centered and mixed-methods: secondary research, an exploratory survey, semi-structured interviews, prototype development, and usability testing. This is not a clinical study, and nothing in it diagnoses anyone. The purpose is to understand an ordinary behavior and evaluate an interaction concept built on top of it.

Phase 1: Secondary Research

The first phase reviews literature across psychology, human-computer interaction, behavior design, personal information management, and AI trust, drawing on Northwestern University Library databases, PsycINFO, and the ACM Digital Library. Its job is to establish the conceptual framework and, just as importantly, to identify what primary research still has to settle rather than letting the solution arrive pre-decided.

Phase 2: Survey and Interviews

Primary research is planned and currently underway. A short survey will collect broad information: what people save, where they save it, how often they return, whether they act, and what gets in the way. Semi-structured interviews with roughly five participants will go after the meaning behind those numbers. Why do they save? What did they picture happening next? How do they feel about opening a collection they have not touched in months? When does a reminder stop being helpful and start being pressure? How much AI involvement feels appropriate before it feels invasive? Participants will be adults who regularly save inspirational or educational content online.

Survey responses will be summarized descriptively and not treated as statistically representative of anything. Interview notes will be coded thematically, with attention to motivations for saving, barriers to retrieval, barriers to action, the kinds of help participants ask for unprompted, and any concern about control or trust. Those themes become design requirements, opportunity areas, and prototype scenarios.

Phase 3: Prototype Evaluation

Once the interactive prototype exists, usability sessions with roughly five to eight regular savers will follow. Tasks will include adding content, reviewing an AI summary, correcting a category the system got wrong, finding an item saved earlier in the session, responding to a suggested topic cluster, deciding whether to accept a Path, and editing the steps inside one. Sessions combine observation with think-aloud commentary and a short debrief.

Evaluation will look at comprehension, retrieval success, perceived accuracy, usefulness, trust, timing, perceived pressure, and sense of control. One comparison matters more than the rest: reactions to a suggestion triggered by a single isolated save versus one triggered by a repeated topic pattern. That contrast should reveal how much evidence a suggestion needs before it feels earned. Sessions will also check whether participants can explain why a suggestion appeared, and whether editable, source-linked steps leave them feeling more capable of starting.

Ethical and Practical Considerations

The research minimizes collection of private saved content. Participants can talk about categories in the abstract or work with neutral prototype examples instead of opening their own accounts. Consent, voluntary participation, and the right to stop will be covered before each session, and findings will be reported in aggregate or anonymized form. Because inference about personal interests can feel invasive even when it is accurate, the prototype foregrounds explanation, correction, dismissal, and opt-in commitment.

Preliminary Research Findings

No survey, interview, or usability data exists yet. What follows comes from secondary research, from working through the problem, and from a conversation with a software-engineering mentor. These are working hypotheses. They are written to be tested and, where wrong, abandoned.

Saving Can Be Its Own Resolution

The most useful reframing so far is that saving may substitute for acting rather than fail at it. Tapping save acknowledges the interest and resolves the small tension of wanting something without having time for it. That would explain a pattern the retrieval framing cannot: a user can sincerely value an item and still feel no urgency about it. If this holds, better search treats a symptom while leaving the missing specifics of action untouched.

A Save Is an Intention With the Specifics Removed

A save records interest and omits timing, context, resources, sequence, and first step. Implementation-intention research predicts that supplying those specifics helps, but only once a person has committed. Pathzn should therefore add structure after the user confirms an interest deserves it, rather than reading commitment into the act of saving.

A Reminder May Reopen Something the User Already Closed

If saving delivers a sense of closure, a generic reminder does not reawaken a goal so much as reopen a loop the person considered finished, which is roughly the definition of nagging. Fogg’s model says the same thing from another direction: a prompt without ability produces nothing. Any useful resurfacing has to arrive with the effort already reduced, meaning a summary, the requirements, a clear first move, and user control over when it shows up.

Deciding When to Intervene Is Harder Than Generating the Content

Mentor feedback made this concrete. Summarizing a video is largely a solved engineering problem. Knowing whether this particular user wants a plan built from it is not. One save is weak evidence of anything. Repeated saves on a topic, recency, revisits, how action-oriented the content is, and whether the person accepted or dismissed similar suggestions before are all stronger signals, but even combined they justify a question rather than a decision. Whether those signals feel understandable and fair is exactly what the prototype needs to find out.

Restraint Is the Feature

The most promising part of this concept is not how much it automates. It is that low-pressure saving stays intact while support appears selectively, for the few things that warrant it. An app that generates a plan from everything has rebuilt the overwhelming to-do list its users were avoiding. Pathzn should notice patterns, offer help, and let the person decide what turns into a commitment.

Proposed Solution

Pathzn is a separate mobile library that receives content a user deliberately shares into it. It does not replace Instagram or TikTok as places to discover things. It adds a layer between saving and acting, where content first becomes understandable and retrievable, and only afterward, and only sometimes, becomes a Path.

How the Experience Works

A user shares a post to Pathzn through the native share sheet, or adds an article or screenshot manually. The app analyzes whatever source information is available and returns a short title, a summary, a suggested category, and any concrete details worth keeping, such as ingredients, equipment, cost, or duration. The user glances at that output, opens the original if something looks off, and edits or accepts it. The item then lands in a visual library organized by category and searchable in plain language.

Most items stop there, which is fine. When several saves form a genuine pattern around one topic, Pathzn explains the pattern it noticed and offers a Path. The user accepts, dismisses, or puts it off. Nothing is created silently. An accepted Path contains a small number of editable, source-linked steps and one realistic first move, plus a light progress state and an optional check-in that stays well short of project management.

Intent-Aware Suggestions

The current concept reads several legible signals rather than treating any single save as a commitment. Candidates include repeated saves on one topic, recency, whether the content is action-oriented, whether related items get revisited, and whether the user accepted comparable suggestions in the past. The prototype will not hide a predictive model behind this. It will use simple, explainable rules, or simulated output where that is cleaner, so reactions can be evaluated before a learning system is worth engineering.

You have saved several videos about starting a home garden. Want to turn them into a Path?

The message has to carry its own justification, so the user understands why it appeared and can judge whether that reasoning is sound. Accepting, dismissing, and postponing all need to be equally easy. A dismissal is not a failure; it is information about relevance, and it is the clearest way a person can say no to a system that made an assumption about them.

Editable, Source-Linked Paths

When a user accepts, Pathzn pulls together the useful material across the related saves, strips duplication, flags what is missing, and proposes a short sequence. Every step stays editable and linked back to where it came from, and extracted facts stay visually distinct from inferred ones. Users can delete irrelevant content, reorder steps, add their own, and rewrite the goal. The AI drafts. It does not decide.

Library and Search

Not every saved item should become a Path, so the library has to be worth using on its own. Summaries, categories, source icons, and meaning-based search do that work. A user should be able to search for “the coffee recipe that used orange peel” and find it without recalling the creator, the caption, or the app it came from. This is what keeps the keep-versus-act distinction honest: plenty of content deserves to be organized and found again while never becoming a commitment.

Resurfacing and Check-Ins

The prototype includes exactly one resurfacing concept, deliberately restrained. It could be a weekly review, a check-in the user schedules, or a prompt tied to a Path already accepted. Nothing in this project assumes more notifications produce more follow-through. Testing will show whether a message arrives with enough context and enough reduction in effort to be worth the interruption.

Design Principles

- The user decides what comes in, what becomes a Path, and what the AI is allowed to change.
- Suggestions explain the pattern or the source behind them.
- Summaries, categories, groupings, and steps can all be corrected or rejected.
- Anything derived from a source links back to it.
- The system does not treat every save as a goal.
- Organizing here should take less effort than the platform folders it supplements.
- Uncertainty is shown, not smoothed over with confident phrasing.

Delivery and Implementation

The deliverable is a working interactive mobile prototype demonstrating the core Pathzn experience. Ten weeks is narrower than a production launch, so the scope is narrower too: Instagram, TikTok, and manually added articles or screenshots. Existing AI APIs will power or simulate the summaries, categories, clustering, and suggested steps. No custom model will be trained.

Prototype Scope

- Onboarding that draws a clear line between saving something and committing to it
- A share and import flow for social posts and manually added content
- AI-assisted title, summary, category, and detail extraction
- A searchable library with source links and editable metadata
- One repeated-topic pattern and the optional Path suggestion it triggers
- At least one generated Path with editable, reorderable, source-linked steps
- A lightweight progress state and a single resurfacing or check-in concept
- Transparency and correction controls throughout, not tucked into settings

Implementation Approach

Development proceeds through iterative UX design with lightweight technical implementation underneath. Research findings become requirements and user flows first. Wireframes then test hierarchy and decision points before any high-fidelity screens exist. The interactive prototype has to feel real enough that participants can judge comprehension, trust, and usefulness without being told what to imagine. Where live AI output is unreliable or simply unnecessary for the research question, controlled prototype responses will be used, so that sessions evaluate the interaction rather than model variance.

A software-engineering mentor will continue advising on feasible data flows, source processing, the boundaries of AI services, privacy, error handling, and eventual scalability. Feasibility shapes design decisions throughout, but production infrastructure, unrestricted platform integrations, and custom model training all sit outside this capstone.

Evaluation Plan

The prototype will be judged against a specific set of questions.

- Do users understand what happens when they add content?
- Are the generated summaries and categories accurate enough to be useful?
- Can users find something again without remembering exact details about it?
- Does a repeated-topic suggestion feel relevant and well timed?
- Can users explain why the suggestion appeared?
- Can users distinguish what they want to keep from what they want to act on?
- Does an editable Path make starting feel more possible?
- Do source links, explanations, and correction controls produce calibrated trust rather than blind acceptance or blanket suspicion?
- Does any part of the experience feel invasive, pressuring, or like another to-do list?

Limitations

A small convenience sample supports formative design insight and represents no broader population. Self-reported saving behavior is likely to diverge from actual saving behavior, particularly around how often people believe they return to things. A prototype can measure comprehension, relevance, and perceived usefulness in a single session; it cannot demonstrate behavior change, which is the outcome the project ultimately cares about. Platform access and content availability may constrain how realistically real posts can be processed, and AI output quality will vary with source quality in ways that controlled prototype examples will not fully expose. The theoretical frameworks have limits of their own. Digital hoarding, implementation intentions, and the Fogg Behavior Model each illuminate part of this behavior, and none of them accounts for the social, emotional, and contextual reasons a particular person saved a particular thing on a particular day.

Next Steps

- Complete the survey and interviews, then synthesize the results into behavioral themes and design requirements.
- Sharpen the keep-versus-act distinction and determine the minimum evidence that makes an intent suggestion feel justified.
- Prototype several suggestion conditions, including an isolated save, a repeated-topic cluster, and a Path the user starts themselves.
- Test onboarding, summaries, semantic search, suggestions, source linkage, editability, and check-in timing with five to eight regular savers.
- Revise based on relevance, trust, perceived pressure, comprehension, and task performance.
- After the capstone, run a longer beta with real saved content to observe repeated use, false-positive suggestions, retention, and actual follow-through.
- Investigate privacy-preserving personalization, platform-specific constraints, confidence displays, accessibility, and the cost of AI processing at scale.

Further iteration will be necessary even if the usability sessions go well. The central question, when assistance should become intervention, cannot be answered in a one-hour session; it needs longitudinal evidence about how suggestions land on the fifth week rather than the first. A successful capstone establishes a credible direction and a product logic worth testing. It does not claim the intention-action gap has been solved.

Conclusion

Pathzn began as an attempt to clean up messy saved folders. Research reframed it around a more interesting tension: saving preserves value and, at the same time, can deliver enough of a sense of completion to make acting feel unnecessary. The responsible response to that is not to convert every interest into work. It is to help people recognize the saves that genuinely matter and make those few specific enough to begin.

The proposed solution combines low-friction capture, AI-assisted understanding, meaning-based retrieval, explainable topic patterns, and optional editable Paths. Whether it works depends almost entirely on restraint. Users have to keep deciding what becomes a commitment, checking information against its source, correcting the AI, and dismissing suggestions without consequence. Primary research and prototype evaluation will test where those boundaries actually sit. The contribution is meant to be two things at once: a product concept, and a design argument for moving saved inspiration toward action without taking agency away from the person who saved it.

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