

Algorithmic Mediation and Consumer Agency: Toward a Theory of Choice in AI-Driven Digital Markets

Vaivaw Kumar Singh

Research Scholar, Faculty of Business Management, Sarala Birla University, Ranchi, Jharkhand, India

DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150900148>

Received: 25 September 2026; Accepted: 30 September 2026; Published: 23 October 2026

ABSTRACT

Artificial intelligence (AI) sits right at the intersection of consumers and markets these days. Algorithms run the show across e-commerce sites, search engines, streaming apps, social media, travel sites, financial tools, and even the latest crop of generative AI assistants. They filter, rank, recommend, personalize, predict—sometimes they even make choices for you. Sure, these tools cut down the avalanche of information and streamline transactions, but they also mess with how people figure out what they like and how they decide.

This paper lays out a theory for how algorithms shape consumer agency, weaving together research from consumer behavior, recommender systems, behavioral economics, algorithmic governance, autonomy, and responsible AI. The main point: agency in digital markets isn't just about picking from a bunch of options. Real agency depends on whether people can actually spot their true alternatives, understand their choices, stick with preferences they genuinely care about, resist algorithmic nudges, go beyond just following recommendations, and really influence the systems that craft their options.

The paper breaks this down into four ways algorithms mediate things: they set up what options you see, guess what you like, steer your behavior, and gradually mold your preferences. From here, the paper introduces the idea of “bounded algorithmic agency”—meaning people still make deliberate choices, but always inside a digital world built and constantly tweaked by platforms and AI. The model says algorithmic systems open the door to efficiency—less time searching, sharper decisions—but also shrink agency by making people feel less in control, killing off chances to explore, and looping back into their preferences.

It flags transparency, the power to challenge recommendations, system setup, preference matching, user skill, and the importance of the decision as core factors that shape these effects. The paper offers ten hypotheses for researchers to dig into and wraps up with this: AI-driven markets demand a fresh take on consumer choice—one that goes beyond the end decision and zeroes in on the systems deciding what's visible, what counts, and what's even possible to pick in the first place.

Keywords: algorithmic mediation, consumer agency, artificial intelligence, consumer choice, recommender systems, personalization, autonomy, choice architecture, digital markets, generative AI

INTRODUCTION

Artificial intelligence is completely changing the way people come across, judge, and respond to the things they find in markets. There's evidence everywhere—in financial services, digital transformation, education, tourism, healthcare, and supply-chain decision making—that AI is stepping out from behind the curtain. It's not just some tool in the background anymore; it's running the show as a go-between for human judgment and choice (Singh et al., 2025; Singh et al., 2026a; Singh et al., 2026b; Mukherjee et al., 2026; Roy et al., 2026; Toshi et al., 2026; Tripathy et al., 2026).

That change matters a lot now that digital markets do so much more than just basic searching and filtering. Markets are charging ahead into a world where AI predicts, personalizes, and even generates new options

entirely. Research on NBFC digital transformation also shows it's not just about getting more efficient; the whole way companies talk to customers and make decisions is changing (Singh et al., 2026a; Singh et al., 2026b; Singh & Sinha, 2026).

This upends the old idea that consumers call the shots. The classic way of looking at things goes something like this: you know what you want, you see what's out there, and you pick what suits you. Straightforward—consumer meets market, makes a choice.

But that model is pretty outdated. Now, algorithms decide what you actually get to see. So, you're picking from a list that the system hands you, not from everything that's actually available.

That's a big deal. Just because a website sells millions of products doesn't mean you actually see more than a handful. Streaming services are packed with thousands of shows, but you only see what gets recommended. Hotel sites list hundreds of places to stay, but most people only look at a couple of "top picks" or "recommended" hotels.

So, it's not just:

What the consumer wants → evaluation → selection.

It's more like:

Market options → algorithm picks and ranks → visible choices → consumer evaluation → selection.

All of this changes how much power consumers really have. You might feel like you've got total freedom while choosing from those five options in front of you, but in reality, you're missing out on tons of choices you never get to lay eyes on. Sure, you're free at the end, but your freedoms boxed in by the system's gatekeeping.

But it's not only about losing control. Digital markets flood you with information—way more stuff than any one person can sort through or even look at. AI can actually help by narrowing things down, showing you what matters, and making choices faster. André and his team (2018) describe the problem like this: AI and Big Data can make life easier and improve well-being, but they can also make people feel like they've lost control.

That's the real back-and-forth here—getting help versus keeping control. This is what defines how we shop, search, and choose in markets ruled by algorithms.

Researchers see it, too. Recommender systems can "anchor" your attention by pushing certain options to the top, which means these tools don't just guess what you like—they can change what you like (Adomavicius et al., 2013). And if people feel like these systems are running their lives for them, they'll push back, even if the systems make life easier (Rohden & Espartel, 2024). Give folks more control—like letting them see a couple recommendations at once—and they're more likely to trust what the algorithm suggests. So, it's not a zero-sum game; you can get autonomy and convenience together (Fink et al., 2024).

But there's an even trickier problem: When preferences are guessed by what people do, but those guesses also change what people do, and those changes drive the next round of recommendations, where do our preferences actually come from? Is AI really discovering what we like, or is it building those preferences as it goes?

Think about someone who clicks on a few political documentaries. The algorithm goes, "Right, you love these," and serves up even more. That person keeps watching, and now the system's sure they're a documentary lover. But maybe they just clicked those because they popped up first. So, are they actually into documentaries, or is the algorithm slowly shaping their taste?

We see these feedback loops all the time. It suggests we can't always act like preferences come first and recommendations just follow along. Sometimes, what we end up liking is built through the back-and-forth with these systems.

This paper brings a new idea into the mix. It calls it “bounded algorithmic agency”—the thought that consumers can make and act on choices, but only within spaces heavily shaped by algorithms that personalize and constantly tweak what's possible.

This isn't about algorithms taking away all your choices. People can skip suggestions, search differently, try other platforms, or even try to “outsmart” the system. But their freedom depends on where algorithms draw the boundaries—what gets shown, what feels relevant, and how hard it is to look elsewhere.

The paper highlights four main contributions:

- First, it argues that algorithmic mediation isn't just a tool—it's a core part of how choices are made now.
- Second, it breaks down four ways algorithms shape things: setting up options, guessing preferences, nudging behavior, and locking in feedback loops.
- Third, it offers a more nuanced view of consumer agency: think visibility of options, decision skills, genuine preferences, freedom to explore, ability to push back, and power to tinker with the system.
- Fourth, it puts forward a model with ten testable predictions about how algorithms can make choices faster and squeeze out consumer agency at the same time.

All of this leads to one big question:

How should we think about consumer agency now that artificial intelligence decides not just which options you prefer, but which ones you ever see, how they're presented, and how your preferences come to life over time?

Research Objectives and Research Questions

The paper sets out to form a hypothesis about how algorithmic mediation shapes consumer agency in AI-driven digital environments.

It tackles five main questions:

- RO1: In what significant ways do AI systems shape consumer decisions before, during, and after the moment of choice?
- RO2: How can algorithmic personalization serve as both a tool to make consumer decision-making more efficient and a factor that limits consumer autonomy?
- RO3: How do we define the multidimensional idea of consumer agency in AI-driven digital spaces?
- RO4: What makes algorithmic mediation act more as an enhancer of consumer agency, rather than a constraint?
- RO5: What theory-based hypotheses can help guide empirical study of AI-mediated consumer decisions?
- Building on these, the paper brings up four research questions.
- RQ1: What mechanisms do AI systems use to change consumer choice models in online markets?

- RQ2: When does algorithmic mediation actually boost consumer agency by lowering search costs and giving more information?
- RQ3: At what point does algorithmic mediation limit consumer agency by constraining visibility, exploration, control, or authenticity of preferences?
- RQ4: What institutional, technological, and consumer-level factors help protect real agency while still letting us benefit from efficient algorithmic decision support?

LITERATURE REVIEW

Consumer Choice, Rationality, and the Construction of Preferences

Standard economic models usually act like preferences are baked in before anyone makes a choice. People are supposed to have a clear ranking in their heads, and just go with what makes them happiest, considering what they know and their limits. But honestly, behavioral research shakes this up. Preferences aren't always fixed. The context matters—a lot.

It depends on how a choice is framed, whether there's an anchor, what the default setting is, how many things you can pick from, what other people are doing, how far away something feels in time, or how everything is laid out. All these little details can totally shift what people choose.

So, choices don't happen in some empty space. The way options are presented—a simple change there can flip the entire decision-making process.

Thaler and Sunstein (2008) talk about this with their idea of “choice architecture.” A choice architect is the one who sets up the place where you make a decision. They don't have to take away choices or make you do anything. Just by deciding how things are arranged, they can steer what happens.

Digital technologies really ramp up the influence of choice architects, since platforms can keep adjusting the decision environment for every single user, all the time. Studies on tech adoption in NBFCs and financial services show the same thing—digital systems change how info, services, and choices show up for users (Singh et al., 2026b; Singh & Sinha, 2026).

Think about a supermarket—every shopper sees the same shelf. But online? That “shelf” can look totally different for everyone.

Mills and Sætra (2022) call this AI-influenced environment “autonomous choice architects.” They point out that AI can pick which kind of interface or recommendations you see—and it's all geared toward a particular goal. The more personalization and random tweaks built in, the more we have to ask—who's responsible for what? Who's accountable? Is anything even transparent?

Digital choice architecture isn't old school anymore:

- First, it leans on data—often tons of it, rich with personal history and context.
- Second, it's personalized—two users see completely different options.
- Third, it's dynamic—the interface changes as you use it.
- Fourth, it's predictive—machine learning guesses what you'll buy, click, or watch, sometimes before you even know.
- Fifth, it's always being refined. Platforms keep running experiments on what to show, then tweak things fast based on what works and what doesn't.

Altogether, this shifts the balance of power between people and whoever is shaping their decisions.

From Nudging to Hyper Nudging

Behavioral nudges are usually just small tweaks in how choices are laid out, like what's set as the default, or the order you see things. Digital platforms take this so much further, because they can change those nudges on the fly.

Yeung (2017) calls these “hyper nudges.” With Big Data and predictive tech, systems keep shaping what you see, based on information about you and even entire groups.

Hyper nudges don't just get set once and left alone. They're always learning and updating. Picture shopping online—and the site watches if you bite at “Only 3 left!” notices, discounts, popularity badges, reviews, or AI-picked suggestions, then keeps adjusting based on how you react.

That means the system isn't just a background—it's like a responsive middleman, always adapting.

But this makes new headaches. Since these nudges are tailored to you, you might not even spot them. Two people “using the same site” could experience worlds apart.

This level of personalization makes ideas about transparency weaker. If everyone sees their own version of the site, just sharing the “general rules” doesn't show what's really influencing your choices.

Recommender Systems and Information Overload

Recommender systems popped up to solve a core problem with digital markets: info overload. In more serious areas like lending, AI models can reduce friction and speed up decisions, showing their power to help (Singh et al., 2025).

Online markets throw so many options at you, no one can sift through them all. Looking through thousands of choices eats up time and energy fast.

That's where recommendations come in. They narrow your choices.

For well-being, narrowing things down actually helps people. Someone overwhelmed by 50,000 products stands a much better chance at a good pick when shown the ten options that matter.

AI helps keep choice manageable—even if you're only choosing between a few things after all.

It's important to think about the gap between every choice you could have, and which options you can actually use.

More choices don't always mean more freedom or better decisions. Too much choice makes things harder, and often less satisfying. Letting algorithms reduce the choices can boost autonomy if it saves people from drowning in options.

André et al. (2018) get right to this tension. AI can streamline choices, but maybe that means users feel less in charge.

So, real agency is about what you can actually use, not how huge your options list is.

Autonomy in Consumer Choice

Autonomy is right at the core of meaningful consumer action.

Wertenbroch et al. (2020) call autonomy central, breaking it into actual and perceived autonomy. That's super important in the age of algorithms.

Sometimes, you technically have a lot of control, but it feels like the algorithm is steering you. Or you might feel free, but actually, your choices are already heavily narrowed or filtered.

So, true freedom and feeling in control don't always match up.

Research still shows people care a ton about autonomy when AI systems are involved.

Fink et al. (2024) ran three studies on AI recommendations. They found people preferred getting a few suggestions over just one, and letting users pick how many suggestions they want made things even better.

It's a big deal—giving users some say doesn't mean they'll reject AI help.

More autonomy actually makes people more likely to accept algorithmic support.

On the same note, studies on AI shopping tools found people want more autonomy—if they feel boxed in, they back off, even if the AI is helpful.

So, efficiency isn't the only thing that matters in using AI. People might avoid useful tools if it feels like they're giving up authorship of their own decisions.

Algorithm Aversion and Algorithm Appreciation

The way people respond to algorithmic advice isn't always negative or always positive.

Dietvorst et al. (2015) found people become wary if they see algorithms make mistakes, even when the algorithms beat human performance. On the other hand, Logg et al. (2019) showed people sometimes trust algorithms over human advice, depending on the context.

So, whether people like or dislike algorithms comes down to specifics.

The real question isn't whether people just trust algorithms, but which tasks, systems, users, and setups foster trust.

Feeling in control shows up here, too.

When users know they can reject, change, or just ignore algorithmic prompts, they're more willing to use them, since they see the system as useful, rather than pushy.

Preference Inference and Behavioral Data

Modern recommenders try to work out what people want by studying what they do. It's the same story with other digital tech—systems use behavioral and operational data to predict, recommend, and make service choices (Singh et al., 2026a; Singh et al., 2026b).

They scoop up what you buy, what you click, what you search for, rate, how long you pause, the order you look through stuff, your device, your location, who you're friends with, and what your profile looks like.

But those are just stand-ins for preferences.

Clicking something could just mean curiosity, not true interest. If you stay on a page a long time, maybe you're confused, not happy. And just seeing stuff more often bumps up interaction without meaning you like it.

So, platforms use proxies, not your real preferences.

Things get messier when what the site is optimizing for isn't what's best for users.

A platform might just want you to stick around, so it pushes out content to keep your session ticking. Stores want sales. Ad platforms want clicks. These might match what you want, but just as often, they don't.

So, an algorithm can guess what you'll do, but still miss what's good for you.

Preference Formation and Recursive Feedback

It gets more tangled when system suggestions start shaping the very behavior the system uses for training next.

Adomavicius et al. (2013) found recommendations act as anchors and can actually change what people think going forward. So these systems are not just reading preferences—they're helping create them.

It goes something like this:

You have a preference → You act on it → The system sees this and tries to figure out what you want → It makes a recommendation → You try new things → What you do next shifts → The system updates its understanding.

The prediction and the nudge are all wrapped up together.

Over time, recommenders can reinforce tastes.

Say you like a product line—you'll see more from it, get used to those options, and end up spending more time there. So, you get more similar recommendations.

Still, that doesn't mean those developing preferences are fake. People's tastes have always changed depending on what they come across.

The real worry is how hard it is to spot what's driving these changes, especially with deep personalization, platform aims, and constant feedback loops.

When people don't know how their environment is engineered, it's hard to understand—or resist—outside influence.

Digital Vulnerability and Power Asymmetries

Algorithm-powered platforms bring power imbalances front and center. And it's bigger than just shopping—AI-driven finance, smart city systems, personalized education, human-AI decision-making—they all make us ask who controls the data, who sets the aims, and who decides how things work (Singh et al., 2025; Toshi et al., 2026; Roy et al., 2026; Tripathy et al., 2026). Digital markets create information gaps. Platforms know loads about users; users know almost nothing about how the system really works.

Digital vulnerability isn't just for the "traditionally" vulnerable. Researchers now see vulnerability as tied to the nature of digital systems and personalization itself.

This shift focuses away from blaming individual choices.

It's not about someone being irrational or uninformed, but about the system being built so that the platform's ability to watch, predict, and steer far outweighs any user's ability to see inside the process.

So, algorithmic power kicks in long before any individual starts making a choice.

Recent studies drive this home across different fields. AI risk pricing in rural non-banking finance ties algorithm-based decision systems to how fast loans get approved (Singh et al., 2025). Research on digital transformation and tech adoption in NBFCs shows digital infrastructures remake not just services but how

people take part (Singh et al., 2026a; Singh et al., 2026b; Singh & Sinha, 2026). There's related work on sustainable growth, climate-aware tourism, metaverse education, smart city healthcare, and circular supply chains saying the same—choices on these platforms feed into much bigger institutional, social, and sustainability goals (Joghee et al., 2025; Mukherjee et al., 2026; Roy et al., 2026; Toshi et al., 2026; Tripathy et al., 2026).

RESEARCH METHODOLOGY

This paper takes an integrative conceptual review and theory-development approach. That fits because algorithmic mediation touches on so many fields—consumer behavior, financial technology, digital transformation in organizations, sustainability, education, and other areas where AI is shaking up how people make decisions (Joghee et al., 2025; Singh et al., 2026a; Mukherjee et al., 2026; Roy et al., 2026; Tripathy et al., 2026).

We're not trying to estimate causal effects using new data. Instead, the study brings together findings and theories from different fields to build a model that explains how consumers make decisions when algorithms come into play.

Conceptual Review Approach

An integrative review makes sense when your research question stretches across several disciplines and the main ideas out there don't quite fit together yet.

People have already looked at algorithmic consumer choice in marketing, consumer psychology, information systems, computer science, behavioral economics, law, philosophy, human-computer interaction, and AI ethics. Each field has its own take. Consumer research dives into autonomy and satisfaction. Information-systems studies look at when people accept recommendations and how much they trust algorithms. Computer science focuses on how accurate recommendations are, how explainable they are, diversity, and building user models. Legal studies look at transparency, manipulation, platform responsibilities, and consumer rights. Behavioral economics analyzes how choice architecture works and how nudges operate. Pulling all these perspectives together is key to building a theory of agency in algorithmic settings.

Analytical Domains

The literature falls into six categories:

- Consumer autonomy and choice—this sets the foundation for understanding what real control and perceived control consumers actually have.
- Recommendation and decision-support systems—this explains how algorithms cut search costs and organize the ocean of information.
- Behavioral influence and choice architecture—these studies show how interface design can tip the scales in decisions.
- Algorithm reliance—research on algorithm aversion and appreciation looks at when people trust or ignore algorithmic advice.
- Algorithmic governance and ethics—this covers opacity, fairness, manipulation, responsibility, and whether consumers can push back against algorithmic decisions.
- Platform and market power—this frames consumer choice in the bigger world of digital platforms and market politics.

Thematic Synthesis

Three questions drove the synthesis:

- What does the algorithm actually control?

- How does that control reshape the way decisions happen?
- Which aspects of consumer agency get stronger or weaker?

Working with these, the synthesis identified four mechanisms of algorithmic mediation and six features of consumer agency.

The four mechanisms are: configuring the choice set, inferring preferences, steering behavior, and shaping preferences over time.

The six dimensions are: making choices visible, enabling competent decisions, keeping preferences authentic, helping with navigation, allowing consumers to challenge outcomes, and letting users control their settings.

These elements make up the conceptual model you'll find in the Findings section.

Nature of the Findings

Since this is a conceptual study, the Findings section only presents theoretical insights from the synthesis—there's no new empirical data here. Think of the hypotheses as starting points that need more research in the future. These can be tested through experiments, surveys, platform audits, long-term studies of consumer behavior, and mixed methods research.

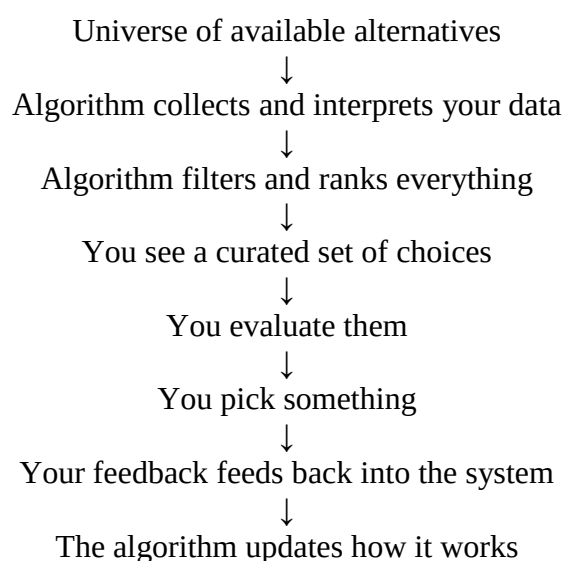
Accordingly, the empirical agenda proposed in Section 12 specifies how the model can be tested through experiments, surveys, mixed-method studies, comparative sector designs, measurement-scale development, and longitudinal research. These designs are intended to evaluate the proposed moderators and boundary conditions rather than to imply that the present conceptual study has already established them empirically.

FINDINGS AND THEORY DEVELOPMENT

Algorithmic Mediation as an Upstream Choice Mechanism

The main point here: algorithms step in before you even start thinking about your choices. Most consumer research focuses on how people actually weigh options and make their pick, but in online markets, the algorithm gets involved way earlier.

Here's how the whole process plays out:



In short, algorithms stand between products and your attention, acting as gatekeepers. That's what we mean by "visibility power."

Basically, whoever controls visibility decides which options you even notice. If you don't see something, you can't pick it. Simple as that.

So, here's the first hypothesis:

H1: As algorithmic filtering gets stronger and more personalized; you see fewer options—because stricter filtering narrows what's visible.

That doesn't always mean fewer options are bad. Sometimes, less clutter means easier decisions. But keep in mind: efficiency isn't the same thing as visibility.

Choice-Set Configuration

Choice-set configuration is about how algorithms pick which options show up for you. This includes ranking, filtering, sorting, recommendations, sponsored placements, personalization, and even how things look on the page.

This process shapes your real possibilities. Sure, you could manually search for other stuff, but since most people just go with what's on the first page, those top suggestions matter most.

Configuration really works through two things: what's right in front of you, and how much effort it takes to find anything else. Options at the top? Easy to check. Ones hidden down below? Not so much—you have to scroll, search differently, and so on.

That's why you can't truly measure consumer choice just by what's "technically available."

Preference Inference

Here's the second mechanism: algorithms have to guess what you like. Recommendation engines can't read your mind; they build models based on what you do.

These guesses can be helpful, but sometimes they miss the mark. The algorithm's suggestions might not really match what you want. An example: if the algorithm is pushing quick engagement, it could distract you from longer-term goals like saving money, managing time, learning something new, or living healthier.

What matters is whether the algorithm's goals line up with yours.

H2: When the algorithm's goals match yours, personalized recommendations actually make you happier.

But when they don't, those recommendations can come off as creepy or manipulative instead of helpful.

Algorithmic Guidance and Decisional Competence

Recommendation systems can make you a better decision-maker by simplifying things. AI support organizes large option sets, highlights what matters, lines up choices side by side, summarizes info, and can spotlight things you'd probably miss on your own.

You see these gains in other areas too, like risk-based pricing and loan approvals, where algorithms speed up judgment calls (Singh et al., 2025).

So, here's what algorithmic mediation does:

- cuts down your search time
- reduces the mental effort
- boosts how relevant the options feel
- makes it easier to compare

- and sometimes, helps you pick better

You might actually become more decisive, even with fewer options to choose from. Research supports this—recommendation engines make choices smoother, though they also sometimes leave you feeling less in control or more uncertain (Rohden & Espartel, 2024).

So:

H3: Some algorithmic help bumps up confidence by trimming down search and avoiding overload.

But with too much automation, you stop exploring on your own, and that balance is key.

The Agency-Constraining Pathway

Funny enough, the same systems that boost competence can shrink your autonomy.

Here's how it plays out:

Algorithmic mediation

- → heavier steering
- → people feel less in control
- → less exploration
- → more dependence
- → less agency

Rohden and Espartel (2024) found that buying with a recommendation agent can actually make you more uncertain, and feeling out of control explains a lot of that.

Other studies agree—how you find options, personalization, and whether you sense you're being manipulated all tie directly back to how in-control or satisfied you feel, with personal autonomy at the heart of it.

So:

H4: When algorithmic recommendations take over, people feel less agency and less control over their own choices.

There's no straight line here: a little algorithmic support is great, but too much is just as bad as too little. In-between is where things work best.

H5: Decision satisfaction peaks at a medium level of guidance—too little, you're lost; too much, you lose agency. Getting the balance right really is the trick.

Behavioral Steering

Algorithms don't just filter options—they steer your actual behavior, too.

Where options are ranked, which ones are set as default, what gets social proof, pop-up nudges, price highlights, timers, tags, and even casual suggestions—it all nudges you toward certain choices.

When the system gets to know you, the nudges get stronger. The platform figures out which tricks work best for you. But even then, you always have the option to refuse a recommendation.

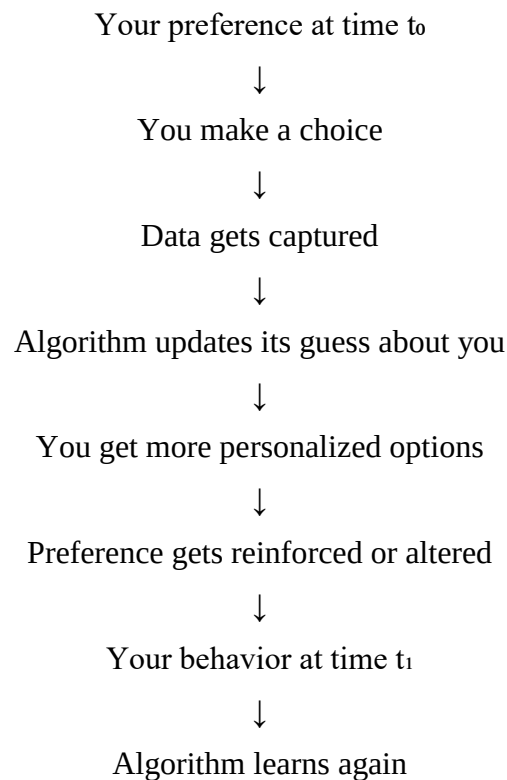
Still, true control isn't just about technically refusing suggestions. If a system knows your weak spots and pokes at them, or distracts you at the wrong times, you're not really exercising free choice.

There's a big difference between persuasion (giving reasons and info) and manipulation (sidelining your ability to decide). Algorithms blur that line—you often don't know why you're seeing a suggestion, so your defenses are down.

Recursive Preference Formation

Now here's the fourth mechanism—recursive preference formation.

Algorithms constantly learn from your actions, but those actions might already be shaped by earlier suggestions. It goes like this:



So, over time, your preferences get locked in—the system puts you in a box and reshapes your feed to fit that box, which only cements things further.

Research backs this up: recommendation systems can lock in consumer preferences, shaping, not just reflecting, your tastes (Adomavicius et al., 2013).

So:

H6: Seeing recommendations that match your supposed tastes over and over anchors your preferences and makes you less likely to try something new, compared to getting a more varied feed.

But keep in mind, reinforcement isn't all bad—it can help you discover what you truly like. Trouble comes when the algorithm reinforces what serves the platform's interests or acts on shaky assumptions.

Preference Authenticity

A big part of feeling in control is believing your choices are really yours.

Here, “preference authenticity” asks: are people aware of, and do they support, the preferences driving their decisions? Real preferences don't appear from thin air—everyone's influenced by something.

The point is, can you look at your choices and say, “Yeah, that's actually what I want.”

Algorithms threaten authenticity if you feel steered too aggressively, or if you sense the system is outsmarting you in ways you can't counter. On the other hand, recommendations can help clarify your goals—especially ones you haven't spelled out yet.

Say, an AI assistant helps you compare using your own criteria—that can feel empowering. If it quietly uses other metrics just to keep you engaged (not to help you), that chips away at your sense of control.

Navigational Agency

Picking among the options you see isn't the same as being able to break out of the default picks.

“Navigational agency” means: can you actually reach other choices beyond what the algorithm puts front and center? You might be “free” to choose any displayed option, but if getting to anything else is too confusing or time-consuming, that freedom doesn't count for much.

This matters now more than ever. Platforms can say, “You can always search manually,” but that ignores the huge impact of rankings and interface design on your real behavior.

So, whether you have real navigational agency depends on how the system is set up.

Contestability

Contestability means you get a say—you can question, tweak, or reject what the algorithm offers.

If the system thinks you want a specific product, you can say, “Nope, not interested,” update your profile, ask for an explanation, or just filter things differently. That's real contestability.

This includes tools like:

- “Not interested” buttons
- Profile editing
- Explaining why you got a certain recommendation
- Preference reset
- Manual filters
- Changing sort order
- Any feedback options

With contestability, you're not just a passive subject; you can push back and steer things.

So:

H7: More contestability dulls the downsides of recommendation overload and helps people feel more agency.

Configuration Control

Configuration control is a level up from contestability—it's about setting the rules, not just vetoing individual suggestions.

Examples: sorting by time instead of by algorithm, dialing up diversity in recommendations, turning off behavioral tracking, hiding ads, or setting the number of recommendations displayed.

Fink et al. (2024) found that when people get to adjust these settings, they actually like and trust recommendations more.

So:

H8: More configuration control makes people more likely to trust and use recommendations because it puts them in the driver's seat.

This is a big lesson for system design: giving users more control doesn't weaken adoption—if anything, it boosts trust.

Transparency as Actionable Understanding

Everyone talks about “transparency” as the cure for black-box algorithms, but just being told “your suggestions are based on your activity and similar users” doesn't move the needle for you.

Transparency matters only when it lets you actually do something.

Think of it in two parts: Descriptive transparency (explains what's going on) and actionable transparency (shows you how to change or react to it).

Studies show people want both—to understand what's happening and to be able to affect it. This varies across cultures and individuals.

Recent work in human-computer interaction says that transparency plus real, hands-on control empowers users' way more than just providing explanations does.

So:

H9: Transparency only increases agency when it comes with real, actionable tools.

Decision Importance and Identity Relevance

How much agency matters depends a lot on what's at stake? Everyday recommendations are one thing, but choices around credit, insurance, college, healthcare, the environment—anything that has a real impact—are another (Singh et al., 2025; Roy et al., 2026; Toshi et al., 2026; Tripathy et al., 2026).

Picking a playlist isn't the same as picking a mortgage, choosing a university, buying insurance, or making a big personal purchase.

People care more about being in charge when the decision says something about who they are.

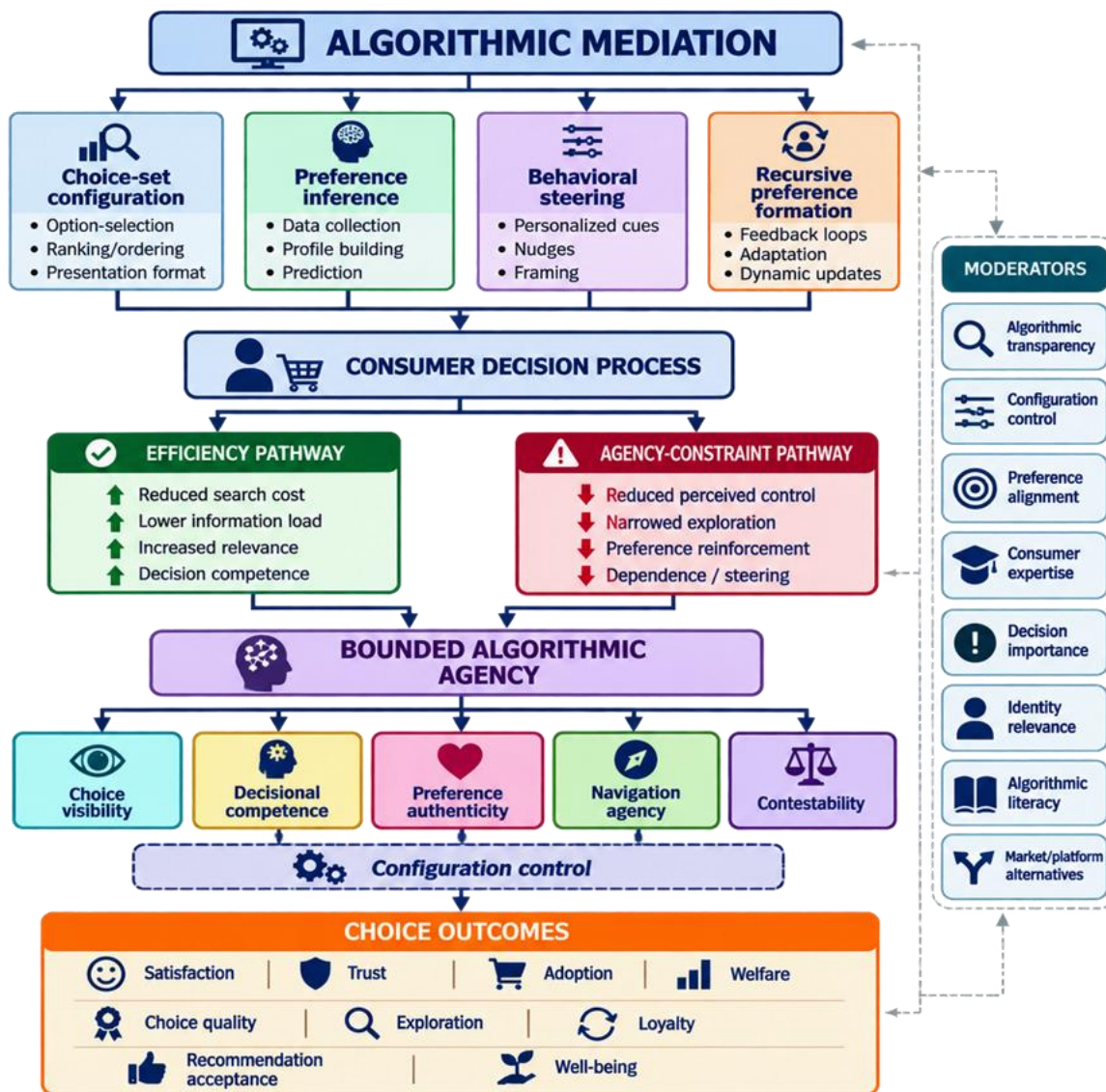
Research says, when choices shape your identity, you're less willing to hand the reins to AI.

So:

H10: The negative effect of too much algorithmic control on your sense of agency is stronger for big, meaningful decisions—and less of an issue for small, everyday choices.

The Conceptual Model

The theoretical relationships can be summarized as this conceptual model:



The main theoretical argument provided here, which is referenced in general by the claim that algorithmic mediation creates effects, is that:

- One is efficiency, the other is lessening the human as the agent.
- Based on which effect prevails, the end effect on consumer welfare can be either positive or negative.
- Can provide a very different view from the 'AI as good'.
- Scenario of "AI is evil".
- It suggests that it is possible for a single AI system to both increase and reduce agency without inconsistencies.

Consider for instance a mathematically-value rationalized recommender system, which acts to become ever more accurate at the considerable cost of imposing limits and disciplining exploration for individual consumers.

The teaser, which is personalized per individual's preferences, not only helps the consumer to overlook more products, because of this maximize choice visibility, but also makes it harder for the consumer to understand the reasons behind the product recommendations, so minimize control if no comprehensible explanations are available.

There are shades of grey that human agency, because of the lack of a pronounced black or white scale.

Toward a Theory of Bounded Algorithmic Agency

The findings really support the idea of bounded algorithmic agency. This basically means that while consumers have some power to shape, weigh, explore, and question their market choices, algorithms are constantly shifting the landscape and shaping what's actually possible.

This brings us to three different kinds of consumer power.

Selection Agency

Selection agency is just about picking from the options you're given. Out of all the types, this is the most limited. Think about a platform that displays ten products and claims you're free to pick whichever you want. That doesn't say anything about why those ten options showed up to begin with.

Navigational Agency

Navigational agency is about how easily you can look beyond what the algorithm serves up. You have strong navigational agency if you can change sorting methods, use different searches, pick categories, or just view everything without personalization getting in the way. On the other hand, if the platform keeps nudging you into certain paths, you've got low navigational agency.

Configurational Agency

Configurational agency is the strongest form. This is where you can actually shape how the system builds your environment. Can you choose what kind of recommendations you get? Can you ask for more variety? Turn off personalization? Tell the system what matters to you? Reset your profile? Spot when something is sponsored? Understand why you see certain things? This kind of agency lets you set the rules, not just play inside them.

DISCUSSION

Rethinking Consumer Sovereignty

This whole framework challenges the old-school belief that consumer sovereignty is just about the final choice. Traditional theory says power is in picking, but in AI-driven markets, the real action happens way before that. If one side shapes what you see and another lets you pick from those, the power splits. Sure, consumers make the final call, but platforms steer almost everything leading up to that point.

So, the easy question—"Did the consumer pick freely?"—misses a lot. More useful questions: What options did the consumer actually find? What information shaped their thoughts? What did the algorithm guess about their preferences? What was the algorithm even trying to do? Could consumers question those guesses or change the ranking?

These show how consumer power really relies on the underlying infrastructure.

AI: Capability and Constraint

The key idea here: don't see consumer agency and algorithmic guidance as opposites. Algorithms can actually make people more capable shoppers. It's the difference between just having freedom and actually being able to use it. If consumers are left on their own, they technically have freedom, but they're stuck with impossible amounts of options. Who wants to scroll through 100,000 items? You drown in choices and can't really decide.

AI helps by turning all that mess into usable choices. We don't want to get rid of algorithms—we want them designed to help people without controlling them. The best systems bring order to chaos but still let users explore, edit, or take charge when they want to.

The Convenience–Agency Paradox

People are always trading control for convenience: autopay, custom playlists, one-click shopping, predictive searching, AI helpers. The smoother it gets, the more we trust in them, and it becomes a loop:

More personalization

- → more relevance
- → more convenience
- → stronger reliance
- → more data
- → even more personalization.

This can make life easier, but it can also turn into dependence. The key is: Can people get out? Can they leave, change the logic, or rebuild their preferences somewhere else? If not, easy slides into sticky, and suddenly you're kind of locked in.

From Recommendation to Delegation

Now, generative AI is pushing things from just recommending to actually doing things for you. Search engines help you find stuff. Recommenders rank the options. Now, generative agents can go ahead and solve problems for you.

It's a progression:

Search → Filtering → Recommendation → Decision support → Delegation → Acting on your behalf

Once you get to delegation, the center of consumer power shifts. People might stop making every little choice and just set the goal and limits. For example:

- "Book the best flight under ₹25,000."
- "Reorder when I'm running low."
- "Pick the cheapest green energy plan."

Now, the power isn't just about picking products, but picking the rules. Consumers pick the criteria their agents should follow.

And that makes it essential who controls those settings. The best agents follow what the user wants; the bad ones follow their owner's interests—probably commercial ones.

The Problem of Objective Alignment

Every recommendation system has a goal—maybe relevance, engagement, revenue, conversion, retention, satisfaction, or some mix. That goal shapes the whole machine. A system that's built to help users isn't the same as one designed to boost profits.

So, the core governance question isn't just "Does the algorithm get the answer right?", but also "Right for what end goal?" High engagement doesn't always mean something good for users. For consumers to hang onto their agency, they need at least some idea what the system is really optimizing for.

Theoretical Implications

This framework matters for lots of research areas.

sConsumer Behavior

It pushes consumer research past the final choice and into all the information-gathering, searching, and doubt that comes first. Studies need to start looking at recommendation design as part of how decisions happen—not just background noise.

Recommender-System Research

It challenges engineers to care about more than just accuracy. Chasing after technical performance scores doesn't tell the full story. We should care about things like: How much variety do users see? Can they fix mistakes in their profile? How easy is it to explore? How much control do users feel? Do their tastes shift over time? Can they undo recommendations?

Algorithm Reliance

This model helps us understand why people sometimes hate—or love—algorithms. It's not just distrust of computers. People often feel left out, like they lost control to the system. But they're happy when algorithms help without taking over.

Choice Architecture

The paper nudges choice architecture theory ahead. Classic choice design was about setting up decision spaces. With algorithms, it's personal, dynamic, adaptive, nearly automatic. The “architect” isn't always a human anymore—it might be a system designing millions of unique experiences.

Digital Market Power

Finally, this theory shifts how we look at platform power: it's not just about prices and market share. It's also about who controls what shows up. Platforms have a huge impact on competition just by shaping what consumers see—even if they don't block transactions directly.

Managerial and Design Implications

Businesses using AI should see consumer agency as a real design and governance goal, not just a legal checkbox. Evidence from NBFC tech adoption shows: digital transformation works when users actually accept, use, and find value in new tech, not just when it's technically available (Singh et al., 2026a; Singh et al., 2026b; Singh & Sinha, 2026).

One way to do this: give consumers multiple options, not just one. More options keep choices real and boost acceptance (Fink et al., 2024).

Next, let users control the personalization—modes like “best match,” “most diverse,” “lowest price,” “new discoveries,” or even “impersonalized” should be at their fingertips.

Platforms can also help users improve their own preferences. For instance, let users say, “No, that's not actually my preference,” even if that's what the system inferred.

Companies shouldn't confuse transparency with long, boring tech disclosures. Good transparency is about highlighting key factors that actually affect users—not dumping the whole system's blueprint.

An AI assistant should be able to just tell you: was this shopping result based on price, satisfaction, advertising, delivery speed, or something else? That kind of clear explanation goes a long way.

Finally, companies should care about long-term trust, not just short-term clicks. Products that support autonomy tend to earn more loyalty—people want to keep using systems they actually control.

Policy and Regulatory Implications

Algorithmic mediation matters a ton for policy too. Regulators used to focus on making sure consumers got the right info and fair practices. But with machine-learning markets, they need to pay close attention to how information is presented and how it guides choices.

The EU's Digital Services Act (DSA) is a big step—it requires platforms to explain major recommendation parameters and, for some platforms, lets users tweak their profiles or change recommendation settings (European Parliament & Council of the European Union, 2022).

Researchers mostly agree regulation shouldn't just chase transparency. Good regulation should combine several algorithmic options. Looking ahead, regulation could add:

- A right to see non-personalized lists,
- Ways to reset or change your recommendation profile,
- Clear info about what's sponsored vs. neutral,
- Simple explanations of why things are recommended,
- Options to switch or combine different recommender systems,
- Protections against manipulative, overly personalized systems.

At the same time, regulators shouldn't just assume that more user control is always better. Too many choices or settings can be overwhelming, not empowering. What works is participation without extra hassle. Setting up user options should feel smooth—not like extra homework.

LIMITATIONS AND FUTURE RESEARCH

This study is conceptual and therefore does not estimate causal effects using new empirical data. Its principal limitation is that the proposed relationships, including the efficiency and agency-constraint pathways, remain theoretical propositions. The framework should consequently be treated as a research program to be tested, refined, and, where necessary, bounded by evidence from different AI-mediated markets.

Empirical Testing of the Theoretical Model

Future research should empirically test the proposed model using complementary quantitative and qualitative approaches. Quantitative studies can use experiments, surveys, field studies, platform audits, and structural equation modelling to estimate the relationships among algorithmic mediation, perceived control, exploration, preference authenticity, decision competence, trust, satisfaction, and recommendation acceptance. Experimental designs could manipulate the strength of algorithmic filtering, recommendation diversity, personalization intensity, explanation quality, and the availability of user controls. Qualitative interviews, think-aloud protocols, digital diaries, and observation can then examine how consumers interpret algorithmic influence, when they experience recommendations as assistance rather than steering, and how they attempt to resist or reconfigure algorithmic systems.

Mixed-method designs would be especially useful because bounded algorithmic agency includes both observable behavior and subjective interpretations of control. For example, an experiment could measure search breadth, recommendation acceptance, time to decision, and switching behavior, while follow-up interviews investigate why participants accepted, rejected, or moved beyond the recommended choice set. Such triangulation would test not only whether the hypothesized effects occur but also the mechanisms through which they occur.

Moderators and Boundary Conditions

The framework should be tested under different levels of algorithmic transparency, user control, digital and algorithmic literacy, personalization intensity, preference alignment, and decision importance. These factors

are likely to determine when algorithmic mediation improves decisional competence and when it constrains agency. Transparency should be operationalized not only as disclosure but as actionable understanding: whether consumers can identify why a recommendation appears and can meaningfully alter the process. User control can be tested through features such as preference editing, recommendation diversity settings, non-personalized modes, profile resets, manual sorting, and the ability to reject inferred preferences.

Digital and algorithmic literacy may shape consumers' ability to recognize ranking, personalization, sponsored placement, behavioral targeting, and feedback loops. Personalization intensity can be varied from non-personalized or lightly personalized interfaces to highly individualized recommendation environments. Decision importance should also be treated as a boundary condition because agency concerns may differ between low-stakes entertainment choices and consequential decisions involving healthcare, education, credit, insurance, or finance. Testing interactions among these moderators would clarify whether the same algorithmic feature has different agency consequences for different consumers and decision contexts.

Measurement Development and Validation

A major priority is the development of validated measurement scales for the paper's central constructs. Bounded algorithmic agency could be developed as a higher-order construct capturing the extent to which consumers can form, evaluate, navigate, contest, and configure choices within algorithmically structured environments. Navigational agency should measure the perceived and actual ability to move beyond default rankings and recommendations, discover alternatives, change search paths, and access non-personalized or differently ordered choice sets. Configuration control should measure the extent to which users can alter the rules governing personalization, data use, recommendation diversity, ranking logic, and preference profiles.

Scale development should proceed through established stages: construct definition and item generation; expert review and cognitive interviews; exploratory factor analysis; confirmatory factor analysis; and tests of reliability, convergent validity, discriminant validity, criterion validity, and measurement invariance. Where possible, self-report measures should be paired with behavioral indicators such as number of alternative searches, use of sorting or reset controls, diversity of options inspected, time spent outside recommended pathways, and frequency of overriding recommendations. This would reduce dependence on perceived agency alone and help distinguish felt control from effective control.

Comparative Research Across AI-Driven Market Contexts

Comparative studies are needed across sectors because the meaning and consequences of algorithmic agency are unlikely to be uniform. E-commerce provides a setting in which ranking, sponsored placement, price, and product variety can be manipulated directly. Entertainment platforms allow researchers to study recommendation diversity, discovery, and taste reinforcement. Finance introduces higher stakes, risk, eligibility, and potential asymmetries in expertise. Healthcare raises questions of vulnerability, professional advice, explanation, and the consequences of delegating judgment. Education provides a context for adaptive recommendations, learning pathways, and longer-term development of preferences and capabilities.

Cross-sector designs should use a common core set of agency measures while allowing context-specific outcomes. This would make it possible to test whether the proposed mechanisms are generalizable or whether their strength changes with stakes, regulation, reversibility of decisions, availability of alternatives, and the degree of human professional involvement. Multi-group analysis or matched comparative case studies could be used to examine whether the structural relationships in the model differ across e-commerce, healthcare, finance, education, and entertainment.

Longitudinal Preference Formation and Consumer Autonomy

The recursive preference-formation mechanism requires longitudinal evidence. Cross-sectional studies can identify associations between personalization and perceived agency, but they cannot establish how repeated exposure changes preferences, exploration, dependence, or autonomy over time. Future research should

therefore follow consumers across repeated interactions with recommendation systems and measure how their stated preferences, revealed choices, exploration patterns, and perceptions of authorship evolve.

Longitudinal panel studies, repeated-choice experiments, digital trace studies, and experience-sampling designs could test whether highly personalized recommendations progressively narrow exploration, stabilize preferences, or instead help consumers discover and articulate preferences that they endorse. Researchers should also examine whether users can reverse or diversify learned profiles after changing settings, resetting histories, or receiving deliberately diverse recommendations. These designs would directly test whether recursive feedback produces preference reinforcement, preference clarification, or path dependence, and under what conditions each outcome emerges.

Additional Research Directions

Cultural and individual differences remain important extensions. Future studies should compare how consumers in different societies value autonomy, convenience, privacy, and algorithmic control, and should examine differences associated with maximizing tendencies, risk aversion, privacy concern, professional expertise, and desire for control. Conversational and generative AI interfaces also requires dedicated study because recommendations embedded in natural-language interaction may make algorithmic mediation less visible than conventional ranked lists.

Finally, multi-agent digital markets create a further layer of agency. When a consumer delegates search, comparison, negotiation, or purchase to an AI agent, agency may shift from selecting individual products to configuring goals, constraints, values, and permissions. Future research should therefore examine whether configurational agency becomes more important as systems move from recommendation to delegation, and how conflicts between consumer objectives, platform objectives, and agent optimization affect consumer autonomy.

DISCUSSION AND CONCLUSION

AI is changing how people make choices. The big shift isn't just that algorithms are better at predicting what you want—it's that AI increasingly stands between consumers and their options, shaping attention, modeling preferences, and driving action. Recent studies in finance, travel, education, smart cities, and supply chains show just how central data-driven, human-AI systems have become to decision-making (Singh et al., 2025; Mukherjee et al., 2026; Roy et al., 2026; Toshi et al., 2026; Tripathy et al., 2026).

Why do algorithms end up dominating the connection between markets and consumers? They decide what gets shown, they guess what people might like, they organize the menu of choices, and they learn from what people actually pick.

That means we need to rethink how we view consumer agency. The old question—does the consumer really have free choice? —just isn't enough. Which options do they even see? How do we figure out what consumers actually want? What criteria shape the design of these automated systems? Can consumers look past the recommended swaps? Do they understand, or question, how the algorithms work? Can they influence the system managing these decisions?

To tackle these questions, the paper uses the idea of bounded algorithmic agency. Consumers still act with intent, but now their choices happen inside a world designed by computers. Four mechanisms explain this shift: how options are framed, how AI infers preferences, how behavior is guided, and how self-perception gets shaped recursively. The model separates pathways that boost efficiency from those that limit agency.

AI can make consumers more empowered by cutting search costs and information overload. But the same technology might also limit autonomy by discouraging exploration, reducing perceived control, and nudging preferences through feedback.

The key takeaway isn't that AI always cuts or boosts consumer agency. What really matters is how mediation works. Systems that keep things open—making their workings visible, contestable, and customizable—can boost consumer power without sacrificing autonomy. On the other hand, some systems offer lots of possible actions but hide competition and keep users from taking real control. That's where agency shrinks.

So, the focus shifts: it's not about freeing consumers from algorithms altogether—that's just not realistic or even desirable. Digital markets are way too complex for people to handle alone. The real challenge is designing AIs that actually enhance, not limit, human agency.

With the rise of generative AI, it's even more urgent. As digital markets move from just searching to recommending to outright delegating choices, consumer agency could shift from deciding what to buy to setting the rules for what chooses on their behalf. Control over “meta-choices”—like defining goals, limits, and values, and configuring how agents decide—might become the new form of consumer sovereignty.

That means future theories of consumer choice need to go beyond basic selection psychology. You have to factor in interfaces, infrastructure, algorithms, feedback, and optimization processes. AI now stands between what's available and what's seen, between preference and prediction, between intention and action.

So, the real question isn't just what people choose. It's how these systems shape what's possible to choose, what's reasonable to think about, and even what becomes desirable.

REFERENCES

1. Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2013). Do recommender systems manipulate consumer preferences? A study of anchoring effects. *Information Systems Research*, 24(4), 956–975. <https://doi.org/10.1287/isre.2013.0497>
2. André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., & Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and Big Data. *Customer Needs and Solutions*, 5, 28–37. <https://doi.org/10.1007/s40547-017-0085-8>
3. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114–126. <https://doi.org/10.1037/xge0000033>
4. European Parliament & Council of the European Union. (2022). Regulation (EU) 2022/2065 of the European Parliament and of the Council of 19 October 2022 on a single market for digital services and amending Directive 2000/31/EC (Digital Services Act). *Official Journal of the European Union*, L 277, 1–102.
5. Fink, L., Newman, L., & Haran, U. (2024). Let me decide: Increasing user autonomy increases recommendation acceptance. *Computers in Human Behavior*, 156, 108244. <https://doi.org/10.1016/j.chb.2024.108244>
6. Joghee, M. V., G., K., Jayamala, C., Lavaraju, B., Manimalathi, P., & Singh, V. K. (2025). Environmental sustainability and economic performance: Evaluating the financial impact on the Indian economy. *Revista Latinoamericana de la Papa*, 29(1), 409–418. <https://papaslatinas.org/>
7. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90–103. <https://doi.org/10.1016/j.obhdp.2018.12.005>
8. Milano, S., Taddeo, M., & Floridi, L. (2020). Recommender systems and their ethical challenges. *AI & Society*, 35(4), 957–967. <https://doi.org/10.1007/s00146-020-00950-y>
9. Mills, S., & Sætra, H. S. (2024). The autonomous choice architect. *AI & Society*, 39(2), 583–595. <https://doi.org/10.1007/s00146-022-01486-z>
10. Mukherjee, S., Salman, S. A., Sukdeo, N. I., Singh, V. K., & Chowdary, V. G. R. (2026). Climate awareness and behaviour of Gen Z travellers: Pathways to achieving Sustainable Development Goals in hospitality and tourism. *International Journal of Tourism Cities*. Advance online publication. <https://doi.org/10.1080/20565607.2026.2663903>

11. Rohden, S. F., & Espartel, L. B. (2024). Consumer reactions to technology in retail: Choice uncertainty and reduced perceived control in decisions assisted by recommendation agents. *Electronic Commerce Research*, 24(2), 901–923. <https://doi.org/10.1007/s10660-024-09808-7>
12. Roy, R., Das, T., Pal, D., Chowdary, V. G. R., Singh, V. K., Mukherjee, S., & Babakerkhell, M. D. (2026). Understanding metaverse use in educational settings: Evidence from students and teachers. *Cogent Education*, 13(1), Article 2689762. <https://doi.org/10.1080/2331186X.2026.2689762>
13. Singh, V. K., Alkhwaldi, A. F., Abu-AlSondos, I. A., Salameh, A. A., Panigrahi, R. R., & Mukherjee, S. (2026). Modelling the effectiveness of technology adoption in NBFCs for the achievement of digital transformation: A structural equation modelling approach. *Scientific Culture*, 12(1.1), 147–164. <https://doi.org/10.5281/zenodo.11425120>
14. Singh, V. K., Shaikh, Z. H., Sinha, K., Panigrahi, R. R., Mukherjee, S., & Chowdary, V. G. R. (2026). From technological revolution to digital transformation in non-banking financial companies: A future research direction. *Journal of Open Innovation: Technology, Market, and Complexity*, 12(1), Article 100712. <https://doi.org/10.1016/j.joitmc.2025.100712>
15. Singh, V. K., Sinha, K., Sahdeo, S. N., Choudhary, N., & Gupta, R. (2025). Impact of AI-driven risk-based pricing on loan approval efficiency in rural non-banking financial services. *Advances in Consumer Research*, 2(4), 3374–3381. <https://acr-journal.com/article/impact-of-ai-driven-risk-based-pricing-on-loan-approval-efficiency-in-rural-non-banking-financial-services-1431/>
16. Singh, V. K., & Sinha, K. (2026). The effectiveness of technology adoption among the customers of Cholamandalam Investment & Finance Company Limited in Jharkhand: An empirical assessment. *Canadian Journal of Marketing Research*, 16(3), 222–242. <https://doi.org/10.61336/r4twgh10>
17. Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.
18. Toshi, K., Verma, A., Chauhan, S. K., & Singh, V. K. (2026). Healthcare ecosystem innovation in emerging smart cities: Co-opetition and public-private partnerships in Ranchi District. *Minnesota Journal of Business Law and Entrepreneurship*, 3, 1102–1135. <https://kommerstad.org/journal/article/view/699>
19. Tripathy, S., Singh, V. K., Rejeb, A., et al. (2026). Meta-analytic study of human-AI co-decision systems and workforce intelligence in enhancing sustainability performance in circular supply chains. *Discover Sustainability*. <https://doi.org/10.1007/s43621-026-04157-x>
20. Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D. R., Matz, S., Nave, G., Parker, J. R., Puntoni, S., Zheng, Y., & Zwebnier, Y. (2020). Autonomy in consumer choice. *Marketing Letters*, 31(4), 429–439. <https://doi.org/10.1007/s11002-020-09521-z>
21. Yeung, K. (2017). ‘Hypernudge’: Big Data as a mode of regulation by design. *Information, Communication & Society*, 20(1), 118–136. <https://doi.org/10.1080/1369118X.2016.1186713>