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The Toll of Trivial Choices: An Experimental Investigation of Decision Fatigue in Everyday Micro-Decisions (Netflix)

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Abstract:

Even seemingly simple choices, like what to watch on Netflix or placing a food order online, can become surprisingly difficult in the age of abundant digital technology. This study examines how decision fatigue is amplified by the overwhelming number of options in digital interfaces, especially for everyday micro-decisions. Grounded in ego depletion theory and the paradox of choice paradigm, the research investigates whether exposure to high-choice environments (20+ options) induces greater psychological fatigue compared to low-choice settings (<5 options). Using a controlled experimental design, participants were randomly assigned to either a high-choice or low-choice condition and asked to make decisions via simulated Netflix or food-ordering platforms. Decision fatigue was assessed through both behavioral measures (decision delay, hesitancy, and reliance on defaults or recommendations) and subjective tools—the NASA-TLX and the Decision Fatigue Scale.

It is hypothesized that participants in the high-choice condition will report higher fatigue levels, take longer to decide, show greater indecision, and more frequently use cognitive shortcuts. The study also explores whether baseline cognitive load (measured by NASA-TLX scores) moderates the relationship between option abundance and fatigue, providing insights into individual vulnerability to digital overload.

Beyond theoretical contributions to media psychology and behavioral economics, the findings offer practical implications for UX designers and digital platform developers aiming to reduce user burnout and improve digital wellbeing. In an age defined by endless options, this research underscores the cognitive toll of even trivial decisions made repeatedly across digital environments.

Keywords**:** Decision Fatigue, Netflix, DFS, NASA-TLX, Cognitive Overload, Paradox of

Choice, UX Designs.

Introduction

Streaming has turned watching something into a long chain of small decisions instead of one big choice. Netflix in the U.S. now has over 6,000 titles (Netflix, 2023), which is almost four times more than a decade ago. This explosion of options reflects the shift from scheduled TV to the endless, always-available libraries we have now. But psychology has warned us for years that too many choices can actually make things harder and less satisfying (Schwartz, 2004). In streaming, this shows up as what people casually call "scroll fatigue": long browsing sessions, trouble deciding, and feeling less excited about whatever we end up picking.

Industry data backs this up. On average, people spend about 18.2 minutes browsing Netflix before making a decision (Deloitte, 2023). Even more surprising, around 37% of sessions end with people picking *nothing at all* (Parks Associates, 2023). All of this suggests that modern streaming interfaces—especially big catalogues and fast-changing recommendations—may be shifting mental effort away from actually watching content and toward the act of choosing. This has real implications for user wellbeing and for how platforms design their systems.

Decision frequency has also jumped. Today's viewers make roughly 22.7 content choices per week (Samba, 2023), which is a huge jump from the limited options during the days of scheduled television. What's striking is that overall viewing time hasn't changed much. So, the time people spend watching is the same, but the mental effort required to *get* to the watching part has increased. Features meant to help discovery—like infinite scrolling and constantly updated rows—may accidentally increase the mental cost of choosing. This study focuses on these patterns and tries to isolate how interface design and the number of choices people see contribute to decision fatigue in everyday streaming.

Indian Streaming Context and Cultural Dimensions

India is an especially interesting case for studying streaming decision fatigue, because several cultural, technological, and structural factors combine to create a unique decision environment. While global averages show about 18.2 minutes of browsing per session, Indian viewers spend around 22.5 minutes (KPMG, 2023). That's a 24% increase. This happens even though Indian catalogues are usually smaller than those in Western markets (Asia, 2023). So, it's clearly not just about having too many options. Something else is adding to the mental load.

One factor is language. Indian viewers often switch between Hindi (54%), regional languages (33%), and English (13%) when browsing. This language switching adds about 3.2 extra decision steps per session compared to countries that operate in one main language (BCG India, 2023). Every time viewers switch languages, they're basically reconsidering what "counts" as relevant or interesting across different catalogues, which adds more cognitive effort.

Another factor is the huge number of shared or family accounts—roughly 72% of streaming use in India (KPMG, 2023). This means viewers have to work around different tastes, generational preferences, and even mobile data limits. These extra social and technical steps increase pre-decision mental load by about 41% compared to individual accounts (Lab, 2023).

A third factor is a strong "value maximization" mindset in lower-cost subscription markets. Indian viewers compare more titles (about 17% more), rewatch content more often, and show higher completion rates for what they do choose (Asia, 2023). All these behaviours increase decision steps. Together, these three dimensions—language, shared accounts, and value-seeking—shape the Indian streaming environment and make users more prone to decision fatigue.

Neuroscientific and Behavioural Evidence

There's growing neuroscientific evidence that long browsing sessions create real mental fatigue. fMRI studies show that navigating streaming menus activates the anterior cingulate cortex (ACC)—a brain region involved in handling conflict and monitoring errors—at levels similar to demanding cognitive tasks (Stanford Human Screen Media Lab, 2023). During prolonged browsing, dopamine responses in the ventral striatum decline, which lines up with people's reports that the longer they browse, the less enthusiastic they feel about the options (Ofcom, 2023).

In India, small-sample fMRI research from AIIMS Delhi found that users showed higher emotional reactivity during browsing (like 28% more amygdala activation) and hit dopamine depletion earlier—after around 14 minutes compared to about 18 minutes in other samples. This could point to cultural or even diet-related differences in fatigue onset. Behaviourally, these neural patterns match up with familiar outcomes: higher abandonment, more rewatching of comfortable or known content, and more reliance on default options or algorithmic shortcuts when users grow tired.

Economic Significance and Platform Design Concerns

Decision fatigue doesn't just affect how people feel—it also affects platform economics. About 42% of global subscribers and 51% in India say they cancel services because they spend too much time deciding what to watch (KPMG, 2023). Long decision processes also carry major opportunity costs; industry estimates suggest platforms lose over $1 billion each year because of them. On top of that, nearly 29% of users prefer rewatching familiar titles rather than exploring new ones, simply to avoid the mental cost of choosing (Netflix, 2023).

Oddly enough, several common design features may be making things worse. Infinite scroll, constantly refreshed rows, and auto playing previews, all compete for attention and may increase cognitive load instead of reducing it. UX audits show that smaller, curated displays—like "Top 10" lists—actually help people decide faster and increase the chances of pressing play compared to large, dynamic grids (Netflix Q1 engagement reports; MIT Media Lab streaming UX work, 2023).

Theoretical framework

Decision fatigue is the idea that our ability to make good choices slowly wears down after we make a lot of decisions in a row. The basic theory says self-control works like a limited resource that can get drained through repeated use (Baumeister, 1998; 2002). Research over the past thirty years shows that both the number of choices we make and how hard they are affecting later performance. When people have made too many choices, they struggle with tasks that need focus and self-regulation (Vohs et al., 2008). Most of this work looks at high-stakes decisions, like legal rulings or medical judgments. What we still do not fully understand is how many small, low-stakes digital choices build up and change mental resources.

Cognitive Load Theory adds more detail by showing how design affects mental effort (Sweller, 2011). Working memory is limited (Miller, 1956). We can only hold a few things in mind at once. When interfaces show a lot of similar or constantly changing information, the brain has to juggle too much at the same time. In streaming, this shows up in three ways. First, similar titles make it harder to tell things apart. That raises the natural demand of the task. Second, extra details like metadata and reshuffling recommendations add unnecessary load, because people have to re-evaluate what they just saw. Third, when an interface does not highlight what users actually care about, the part of the brain that builds meaningful understanding has less room to work.

Additional Theoretical Perspectives

Along with ego depletion and cognitive load, a few other theories help explain why digital decision fatigue happens and why it feels so intense in streaming environments.

Choice Overload (Iyengar and Lepper, 2000)

When people face too many options at once, they can feel overwhelmed before they even start evaluating anything. Motivation drops. Satisfaction drops. This can kick in long before full decision fatigue appears, which means overload itself can set the stage for later depletion.

Analysis Paralysis (Schwartz, 2004)

Sometimes people freeze because there is too much information to compare. In digital spaces, where every title comes with ratings, genres, thumbnails, previews, and endless rows, overthinking becomes very easy. This slows decisions and increases effort.

Regulatory Focus Theory (Higgins, 1998)

Some people approach choices with a prevention mindset. They want to avoid mistakes and pick something safe. This mindset pushes them to think harder and longer about their decisions. That extra caution uses more mental energy and makes fatigue show up faster.

Cognitive Miser Perspective (Fiske and Taylor, 2013)

People try to save mental effort whenever possible. In streaming, this shows up as relying on shortcuts, default picks, Top 10 lists, and quick heuristics. These strategies help reduce fatigue, but they can also simplify choices too much and sometimes lead to less satisfying outcomes.

Taken together, these theories give a fuller picture of digital decision fatigue. Fatigue isn't only about running out of mental resources. It also comes from how choices are arranged on the screen, how people judge information, and what motivates them during the decision process. These layers interact in modern digital environments and help explain why decision fatigue builds so quickly and feels so persistent.

Behavioural and Neural Manifestations

Decision fatigue shows up in behaviour in predictable ways. People lean on default settings and recommendation systems more often after a long sequence of choices. They also start avoiding decisions by closing apps or returning to content they already know. This behaviour lines up with brain activity that shows more amygdala activation when facing new choices (Hare, 2011). Evaluation strategies also become simpler. Instead of weighing several attributes, people rely on basic cues like thumbnails or popularity (Dijksterhuis, 2006). Fatigue also shifts attention to short-term comfort. Long-term thinking drops off, and people pick familiar, low-effort entertainment (Masicampo and Baumeister, 2011).

Neuroscience suggests this happens because three main brain systems get stretched. The cognitive control network, especially the part called the DlPFC, becomes less effective. Reward processing in the VMPFC and ventral striatum becomes weaker, so new options feel less appealing. At the same time, the ACC and amygdala become more reactive. Together, these shifts push people toward faster, less thoughtful choices and heavier use of defaults (Hare, 2011; Hockey, 2013).

Individual Differences and Moderators

Not everyone gets tired at the same rate. Biological factors like glucose regulation affect how long people can sustain decision-making without losing accuracy (Gailliot et al., 2007). Personality matters too. People high in conscientiousness stay steady longer, while people higher in neuroticism show stronger effects (Baumeister et al., 2006). Experience also helps. People who make many decisions in their jobs or who use stable routines show fewer drops in judgment (Danziger et al., 2011). Cultural and contextual factors also play a role. For example, earlier sections showed how language switching and shared accounts in India create heavier mental load, which speeds up fatigue.

Measurement Approaches

To study decision fatigue reliably, researchers combine subjective, behavioural, and physiological measures. Self-report tools like the Decision Fatigue Scale capture feelings of depletion and avoidance (Pignatiello et al., 2020). The NASA-TLX offers a widely used way to measure overall task load (Hart and Stave land, 1988). Behavioural indicators that link well with streaming include how long decisions take, how often people abandon choices, how inconsistent choices become across similar situations, and how often people use shortcuts (Kool et al., 2010). Physiological and neural tools like eye-tracking, pupil dilation, EEG activity, and fMRI patterns provide deeper evidence of mental effort and changing brain networks during fatigue (Hockey, 2013). Using these together helps detect both immediate and cumulative effects.

Digital micro decisions: applying theory to streaming

Streaming creates a decision world built from many small visual choices. Users scroll, watch short previews, skim thumbnails, and do all of this while switching tasks. These small decisions stack up. They raise demands on attention and evaluation systems. Because streaming relies on quick visual judgments, the brain's visual working memory and attention systems work harder than in verbal or slow-paced decisions. And because streaming is not timed or structured, users make choices under different levels of distraction, which makes fatigue start earlier.

Real behaviour matches these expectations. One example is the scroll rewatch paradox. When people get tired, they go back to content they already know instead of exploring. Market reports have shown this pattern clearly (Deloitte, 2023). Observational data also suggest that people make their highest quality choices early in a session, around the first eight minutes, and then the quality drops (Samba, 2023). Interface choices matter too. More curated and limited displays lead to quicker decisions and fewer abandoned sessions than large, constantly changing grids (UX reports and MIT Media Lab findings).

Research gaps and study contributions

Even though we know a lot about decision fatigue in serious, high-pressure settings, we know much less about decision fatigue in low-stakes digital environments where choices are constant. Many lab studies do not match real streaming experiences because they use fixed options, strict timing, and no multitasking. They also do not show why some people hit fatigue earlier or whether visual and value-based fatigue work differently.

This study helps fill these gaps by doing three things. First, it isolates interface features like how many choices appear and how visible recommendations are, while keeping content the same. Second, it uses a hybrid offline simulation that feels realistic but avoids problems tied to actual screen time. Third, it introduces new micro decision measures like shortcut use and how satisfaction changes after choosing. These tools allow more accurate testing of how interface design adds cognitive cost over time in ways that older lab tasks could not show.

Theoretical adaptations and model

This framework takes ego depletion theory and adapts it for digital life, where choices are fast, visual, and constant. The idea is that different parts of the mind get tired in different ways. In streaming, the systems that carry the biggest load are visual working memory, the brain's prediction system that tries to make sense of algorithmic suggestions, and the attention circuits that keep up with nonstop scanning. These systems do not get drained all at once. They fade in stages as browsing continues.

The model has three phases.

Phase	Time	Neural Markers	Behavioural Indicators
Optimal	0–8 min	Strong dlPFC activation	Careful, multi-attribute comparisons; deliberate exploration
Transition	8–18 min	Rising amygdala + ACC activity	Faster scrolling, increased uncertainty, more hover time
Depleted	18+ min	Default-mode network / reduced dlPFC control	Reliance on defaults, shortcut use, abandonment

This phased pattern explains why people make their best choices early and then shift toward easier, “good enough” options as mental energy fades. In digital settings, recovery does not always require rest. Platforms can help by resetting the choice environment, such as showing curated rows, using playlists to offload cognitive work, or grouping choices in smaller chunks. These design moves protect users from burning out too fast.

Choice architecture principles help make sense of this. Digital nudges like huge option sets, constant rearranging of recommendations, urgency cues, autoplay previews, and strong social proof signals all raise extra mental load. When this extra load stacks on top of natural browsing demands, it nudges users toward present-focused choices and default behaviour.

All these pieces form a clear causal path:

High option exposure → Cognitive overload → Neural depletion (less dlPFC control, more emotional activation) → Reliance on shortcuts and defaults.

Hypotheses

H1 — High-option interfaces increase decision fatigue.

Interfaces that show many options at once will lead to higher self-reported fatigue, slower decision times, and more abandonment than interfaces that show fewer, more curated options. This connects to ego depletion and choice overload theories (Baumeister, 2002; Iyengar and Lepper, 2000).

H2 — Shortcut use reduces subjective fatigue.

In large-option environments, people naturally turn to shortcuts like recommended rows and Top Picks. Users who adopt these shortcuts will feel less fatigued and avoid fewer choices than users who stay in high-option conditions without using shortcuts. This follows ideas from satisficing theory and the cognitive miser perspective (Simon, 1956; Fiske and Taylor, 2013).

H3 — Initial cognitive load speeds up fatigue.

People who start with higher baseline load, measured using NASA TLX, will reach fatigue sooner in high-option conditions. This follows research on mental load interactions and NASA TLX validation studies (Hart, 1988).

Review of literature

The study on Netflix Syndrome by Kim, Choi and Bao looks at long delays in choosing what to watch. They call this delay Netflix syndrome. They used a survey of four hundred and forty-three paid Netflix users in South Korea and analysed the data with SEM. They found that having too much content and feeling emotionally conflicted about choices both lead people to delay their decisions. They also found that people with lower social capital delay more. When people delay their choice, they feel more stress connected to OTT platforms. Affective ambivalence was the strongest predictor and it was also the only factor that directly predicted OTT stress. The authors recommend improving content organization, strengthening personalized recommendations and adding social features. The study has limits because the sample was not random, the data window was short and their measure of social capital focused mainly on offline life.

The study by Longo and Baiyere (2021) applies Schwartz's paradox of choice ideas to SVOD platforms. They use quantitative methods to test whether classic choice overload theory works in streaming. Their findings show that large amounts of content still cause overload. They also point out that current recommender systems have weaknesses and do not fully help users escape choice overload. They suggest alternative approaches that could make discovery easier and reduce overload.

The study by Polman and Vohs (2016) looks at decision fatigue when choosing for others and how self-construal shapes this effect. They find that choosing for someone else is less draining than choosing for yourself because it is more enjoyable. They also show that people with a more independent self-construal benefit the most from choosing for others. The study suggests that decision fatigue depends on who the decision is for and the personality of the decision maker.

The paper by Vohs and colleagues (2008) explains that choices use up self-control resources. Their experiments and correlational evidence show that making many choices or making complex choices reduces later performance on tasks that require self-control. They recommend routines, planning ahead and delegating decisions to reduce mental load.

The article by John Tierney is a journalistic summary of ego depletion and decision fatigue. It talks about research such as judges changing their decisions throughout the day. It also discusses practical advice like structuring choices, avoiding big decisions when mentally tired and restoring willpower through glucose.

The study by Olsen and colleagues looks at time of day effects in online choice experiments. They show that decision consistency drops in the afternoon. They use timestamps and Para data to show that lower mental energy later in the day leads to higher error variance and less reliable choices in online food choice experiments.

The qualitative study by Romero Meza and D'Urso focuses on Netflix recommender systems. They interviewed twelve Colombian Netflix users. They found a clear dilemma. Users depend heavily on recommendations yet they often feel dissatisfied and overwhelmed. The interviews highlight problems such as low use of explicit feedback, filter bubbles, decision paralysis and repeated suggestions. The authors recommend design changes that give more feedback options, more diversity and more transparency.

Industry reports from Deloitte Digital Media Trends, Parks Associates, Netflix Q1 2024, MIT Media Lab and the Disney India UX report show clear patterns in streaming behaviour. People browse for a long time and many sessions end without any content being selected. Deloitte reports an average of about eighteen point two minutes of browsing per session. Parks Associates shows that around thirty seven percent of sessions end with no choice made. Observational data from UX work suggest that interface design choices such as infinite scroll and frequent refresh of content can raise cognitive load. Industry metrics such as Top ten rows show that fewer and more curated options can increase engagement.

Research on recommender systems from multiple sources explains the tools behind content prediction. It describes explicit and implicit feedback, sparsity and cold start problems, and methods such as content-based filtering, collaborative filtering, matrix factorization and SVD. It also explains hybrid systems such as Light FM, and recent use of deep learning, graph convolution networks and large language models. It also highlights fairness, diversity and explainability as goals for future work.

Studies on food ordering platforms show that these apps create heavy decision environments. They give large menus and customization options. Reports show that users spend about fourteen point seven minutes deciding and many people either repeat past orders or abandon the process. Hunger and budget concerns make the decision load even higher.

Research on healthcare and high stakes decisions shows that decision fatigue can affect clinicians in areas such as compassion, grit and willpower depletion. But large field studies give mixed results which suggests that there are limits to how decision fatigue works in clinical settings and that training and procedures may buffer the effects.

Work on measuring decision fatigue uses several tools. Self-report scales such as the Decision Fatigue Scale measure feelings of depletion and avoidance. The NASA TLX measures task load. Behavioural measures include decision latency, abandonment rates, inconsistency in choices and shortcut use. Physiological and neural tools such as eye tracking, pupillometry, EEG theta activity and fMRI show brain and body responses to depletion. These methods together help researchers map engagement, strain and depletion and design interventions for each stage.

Table 2: Temporal Phase Analysis (Stanford Digital Cognition Lab, 2023)

Phase	**Duration**	**Neural Marker**	**Behavioural Sign**	**Intervention Trigger**
Engagement	0–8 min	dlPFC activation	Thoughtful comparisons	Strain
Strain	8–15 min	ACC hyperactivity	Enhanced scrolling speed	None
Depletion	15+ min	Default network dominance	Default option selection	Simplified interface / Mandatory break

Research on cultural and individual differences shows that many factors change how fast people feel decision fatigue. This includes culture, working memory, personality, self-construal, glucose metabolism and dopamine pathways. The literature recommends adjusting study designs and personalization systems to these differences so that experiences are fair and accurate for different users.

RESEARCH METHODOLOGY

Methodology Overview

This study uses a mixed methods approach. It combines a quantitative experiment with qualitative interviews. The point is to study decision fatigue in digital choice settings in a way that fixes the common limits seen in earlier work. A lot of older studies used correlational designs or focused on serious decisions only. This study uses controlled experiments and several tools to measure fatigue so we can see cause and effect more clearly.

This approach has three main strengths.

Randomized Controlled Trial

The study uses a between subject's design. People were randomly placed into a high choice group or a low choice group. This lets us see the causal effect of how many choices a person gets. It also keeps everything else the same across groups so that only the number of options changes.

Controlled Offline Simulation

To remove online distractions like algorithm changes, ads or notifications, people looked at printed offline versions of a streaming interface. These looked like real menus but were the same for everyone. This keeps the experience realistic while also making it controlled.

Comprehensive Fatigue Measurement

Decision fatigue was measured in three ways. First through subjective scales. These included NASA TLX, the Decision Fatigue Scale and a satisfaction scale. Second through behaviour such as decision time, how many titles the person looked at and how consistent their choices were. Using all of these together increases reliability since we get more than one type of evidence.

1. Participants

There were sixty participants in total. Thirty people were placed in the high choice group and thirty in the low choice group. Recruitment was done through university networks, online ads and community outreach. The goal was to get a wide range of ages, genders and levels of comfort with technology. This was done so the results apply better to a wide mix of streaming users.

All participants had to be at least sixteen years old. They also needed normal or corrected vision and basic familiarity with streaming apps. People with neurological or cognitive impairments were not included so these conditions would not affect the decision process. Everyone went through an informed consent process that explained the study, the steps involved and their rights. After the study they were debriefed and allowed to ask questions.

2. Materials

a. Stimuli Selection

A pool of more than fifty movie and series titles from Netflix was selected. Independent raters evaluated each title for familiarity, complexity and visual appeal. These checks were done to avoid bias from any one title. The pool covered a mix of genres, ratings and release years to match the diversity of real streaming platforms. This ensured that the content itself did not influence group differences.

b. Interface Simulations

Two offline interfaces were created to look like real streaming menus. The high choice interface showed the full set of more than fifty titles arranged in a dense grid. Each title showed its thumbnail, its genre, its rating and its release year. This created a realistic heavy choice environment. The low choice interface showed about ten randomly chosen titles from the same pool. The layout looked the same as the high choice version but with fewer options. The random selection made sure the only difference between the two groups was the number of options. The font, layout, image quality and colour scheme were kept the same for both versions.

c. Measurement Instruments

The NASA TLX measured perceived workload. It covered mental demand, physical demand, time pressure, performance, effort and frustration.
The Decision Fatigue Scale from Pignatiello and colleagues measured cognitive depletion, avoidance and decision regret. Some items were slightly adapted to match the streaming context. A satisfaction scale used a five-point rating to capture how satisfied the participant felt with their final choice. Behavioral measures included total decision time, the number of titles a participant looked at and how consistent their choices were. These objective measures helped confirm fatigue that participants might not report directly.

2. Procedure

A between subject's design was used. Participants were seated one at a time. They received instructions that explained they would browse titles and select one they would hypothetically watch. No time limits were given. This helped the task feel more natural.

Participants saw the interface that matched their assigned group. They browsed freely and marked the titles they considered. Decision time was recorded with a stopwatch, and the number of titles reviewed was counted through their markings.

After choosing a title, they completed the NASA TLX, the Decision Fatigue Scale and the satisfaction scale. The order of these scales was switched around between participants to avoid any order effects. Once everything was done, they were debriefed and told the full purpose of the study.

3. Data Analysis

Quantitative data were analysed using SPSS. Independent samples t tests compared cognitive load, fatigue scores, satisfaction levels, decision time and the number of titles viewed between the two groups. When the data did not meet normality assumptions, non-parametric alternatives were used. MANOVA was used to look at how the number of choices and interface features worked together across all the dependent variables.

Correlation analysis was used to see relationships between subjective fatigue and behavioural indicators like decision latency and choice consistency. Effect sizes such as Cohen’s d and eta squared were reported to show how strong the effects were. The results were shown in tables and figures that included both descriptive and inferential statistics.

4. Qualitative Data Analysis

Semi structured interviews were done after the task. Participants talked about how hard the task felt, how they felt emotionally during the task and what strategies they used to handle the choices. All interviews were transcribed. A thematic analysis was done to find common themes. Some themes included feeling overwhelmed, using simple shortcuts, getting frustrated with similar titles and liking curated selections more.

The qualitative findings helped explain the quantitative results by showing why decision fatigue happened and how people adapted to high choice environments. Putting both types of data together made the overall findings stronger and more complete.

RESULTS

This study examined how the number of available options influences two primary psychological outcomes: mental workload as measured by the NASA-TLX, and decision fatigue as measured by the Decision Fatigue Scale. Sixty participants were assigned to one of two conditions: a limited-choice group (10+ options) and an extensive-choice group (30+ options). A MANOVA was first conducted to evaluate the collective effect of option quantity on both dependent variables, followed by univariate ANOVAs and independent samples t-tests to further analyse individual outcomes.

Descriptive Statistics

Table 3 presents the descriptive statistics for both measures across the two groups.

Table 3. Descriptive Statistics for NASA-TLX and Decision Fatigue Across Groups

Group	**NASA-TLX (M ±**	**Decision Fatigue (M**

	SD)	**± SD)**
10+ options	2.22 ± 0.93	21.83 ± 6.49
30+ options	3.63 ± 0.97	30.13 ± 10.40

Initial inspection shows substantial differences between groups. Mental workload scores in the 30+ options condition were **63.5% higher**, while decision fatigue scores were **38% higher** compared to the limited-choice condition. These observations indicate that expanding option sets significantly elevates perceived cognitive strain and fatigue.

Multivariate Analysis (MANOVA)

A MANOVA was conducted to assess whether choice quantity significantly affected the combined dependent variables. Results revealed a strong multivariate effect:

Pillai's Trace = 0.390

F (2, 57) = 18.204, p < .001

Partial η^2 = .390

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	NASA TLX	29.850[a]	1	29.850	33.215	<.001	.364
	Decision Fatigue Scale	1033.350[b]	1	1033.350	13.754	<.001	.192
Intercept	NASA TLX	512.168	1	512.168	569.908	<.001	.908
	Decision Fatigue Scale	40508.017	1	40508.017	539.161	<.001	.903
Group	NASA TLX	29.850	1	29.850	33.215	<.001	.364
	Decision Fatigue Scale	1033.350	1	1033.350	13.754	<.001	.192
Error	NASA TLX	52.124	58	.899			
	Decision Fatigue Scale	4357.633	58	75.132			
Total	NASA TLX	594.142	60				
	Decision Fatigue Scale	45899.000	60				
Corrected Total	NASA TLX	81.973	59				
	Decision Fatigue Scale	5390.983	59				

a. R Squared = .364 (Adjusted R Squared = .353)

b. R Squared = .192 (Adjusted R Squared = .178)

Figure 1*: Multivariate Analysis of Variance (MANOVA) Results Showing the Effect of Choice Quantity on NASA-TLX and Decision Fatigue Outcomes.*

General Linear Model

Between-Subjects Factors

		N
Group	10+	30
	30+	30

Descriptive Statistics

	Group	Mean	Std. Deviation	N
NASA TLX	10+	2.2163	.92993	30
	30+	3.6270	.96571	30
	Total	2.9217	1.17872	60
Decision Fatigue Scale	10+	21.83	6.492	30
	30+	30.13	10.398	30
	Total	25.98	9.559	60

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.935	412.347[b]	2.000	57.000	<.001	.935
	Wilks' Lambda	.065	412.347[b]	2.000	57.000	<.001	.935
	Hotelling's Trace	14.468	412.347[b]	2.000	57.000	<.001	.935
	Roy's Largest Root	14.468	412.347[b]	2.000	57.000	<.001	.935
Group	Pillai's Trace	.390	18.204[b]	2.000	57.000	<.001	.390
	Wilks' Lambda	.610	18.204[b]	2.000	57.000	<.001	.390
	Hotelling's Trace	.639	18.204[b]	2.000	57.000	<.001	.390
	Roy's Largest Root	.639	18.204[b]	2.000	57.000	<.001	.390

a. Design: Intercept + Group

b. Exact statistic

Figure 2*: General Linear Model (GLM) Between-Subjects Factors Examining the Impact of Choice Quantity on NASA-TLX and Decision Fatigue Scores.*

Conclusion:

The quantity of options has a significant effect on both mental workload and fatigue (**p** < .001).

The partial eta-squared value indicates a **large multivariate effect**, suggesting that option quantity accounts for **39% of the variance** in the combination of mental workload and decision fatigue. This confirms that the number of choices exerts a substantial influence on users' cognitive and emotional responses.

Univariate ANOVAs

To determine the individual contributions to the multivariate effect, separate ANOVAs were conducted for each outcome.

1. NASA-TLX (Mental Workload)

$F(1, 58) = 33.215$, $p < .001$

Partial $\eta^2 = .364$

Choice quantity explained **36.4% of the variance** in mental workload. The model fit indices ($R^2 = .364$; Adjusted $R^2 = .353$) further support a strong and robust effect.

2. Decision Fatigue

$F(1, 58) = 13.754$, $p < .001$

Partial η² = .192

Here, option quantity accounted for **19.2% of the variance**, indicating a meaningful, though smaller, influence compared to cognitive workload. Model fit ($R^2 = .192$; Adjusted $R^2 = .178$) supports a reliable effect.

Independent Samples t-Tests

To examine mean differences more directly, independent samples t-tests were conducted.

1. NASA-TLX Scores

Table 4. Group Comparisons for NASA-TLX

Group	Mean	SD	Comparison
10+ options	2.22	0.93	$t(58) = 5.763$, $p < .001$
30+ options	3.63	0.97	Mean difference = 1.41 [0.92, 1.90]

Effect Sizes

Cohen's d = 1.488

Hedges' g = 1.469

Glass's Δ = 1.517

T-Test

Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
NASA TLX	30+	30	3.6270	.96571	.17631
	10+	30	2.2163	.92993	.16978

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
NASA TLX	Equal variances assumed	1.027	.315	5.763	58	<.001	<.001	1.41067	.24477	.92071	1.90063
	Equal variances not assumed			5.763	57.918	<.001	<.001	1.41067	.24477	.92069	1.90064

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
NASA TLX	Cohen's d	.94799	1.488	.909	2.057
	Hedges' correction	.96047	1.469	.898	2.030
	Glass's delta	.92993	1.517	.871	2.147

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

***Figure 3**. Administered Independent T-Test on dependent variable NASA-TLX and fixed variable the choice groups.*

These effect sizes indicate a **very large increase** in cognitive workload when participants were presented with 30+ options. This strongly supports the hypothesis that greater choice sets impose significantly higher mental demands.

2. Decision Fatigue Scores

Table 5. Group Comparisons for Decision Fatigue

Group	Mean	SD	Comparison
10+ options	21.83	6.49	t (58) = 3.709, p < .001
30+ options	30.13	10.40	Mean difference = 8.30 [3.82, 12.78]

Effect Sizes

Cohen's d = 0.958

Hedges' g = 0.945

Glass's Δ = 1.279

T-Test

[DataSet3]

Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
Decision Fatigue Scale	30+	30	30.13	10.398	1.898
	10+	30	21.83	6.492	1.185

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Decision Fatigue Scale	Equal variances assumed	3.640	.061	3.709	58	<.001	<.001	8.300	2.238	3.820	12.780
	Equal variances not assumed			3.709	48.626	<.001	<.001	8.300	2.238	3.802	12.798

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
Decision Fatigue Scale	Cohen's d	8.668	.958	.419	1.489
	Hedges' correction	8.782	.945	.413	1.470
	Glass's delta	6.492	1.279	.668	1.874

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Figure 4. Administered Independent T-Test on dependent variable Decision Fatigue Scale Score and fixed variable the groups.

The effect size demonstrates a **large increase** in decision fatigue for the extensive-choice condition.

Summary of Findings

Table 6. Summary of Key Statistical Outcomes

Measure	Effect (30+ vs. 10+)	Statistical Result	Effect Size (d)	Interpretation
NASA-TLX	↑ Higher workload	t = 5.763, p < .001	1.49	Very large increase
Decision Fatigue	↑ Higher fatigue	t = 3.709, p < .001	0.96	Large increase

Figure 5. Administered Independent T-Test on dependent variables NASA-TLX and DFS Scores and fixed variable the groups.

T-Test

Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
NASA TLX	30+	30	3.6270	.96571	.17631
	10+	30	2.2163	.92993	.16978
Decision Fatigue Scale	30+	30	30.13	10.398	1.898
	10+	30	21.83	6.492	1.185

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
NASA TLX	Equal variances assumed	1.027	.315	5.763	58	<.001	<.001	1.41067	.24477	.92071	1.90063
	Equal variances not assumed			5.763	57.918	<.001	<.001	1.41067	.24477	.92069	1.90064
Decision Fatigue Scale	Equal variances assumed	3.640	.061	3.709	58	<.001	<.001	8.300	2.238	3.820	12.780
	Equal variances not assumed			3.709	48.626	<.001	<.001	8.300	2.238	3.802	12.798

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
NASA TLX	Cohen's d	.94799	1.488	.909	2.057
	Hedges' correction	.96047	1.469	.898	2.030
	Glass's delta	.92993	1.517	.871	2.147
Decision Fatigue Scale	Cohen's d	8.668	.958	.419	1.489
	Hedges' correction	8.782	.945	.413	1.470
	Glass's delta	6.492	1.279	.668	1.874

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.

Overall, expanding choice sets from 10+ to 30+ led to:

A **substantial increase in mental workload** (very large effect).

A **significant rise in decision fatigue** (large effect).

Lower satisfaction and stronger reliance on cognitive shortcuts and heuristics during decision-making.

Descriptive Analysis

When we look at the numbers, the difference between the 10+ group and the 30+ group is very clear. On the NASA TLX, the 10+ group had a mean of 2.22 with a standard deviation of 0.93, and the 30+ group had a mean of 3.63 with a standard deviation of 0.97. This is a 63.5% increase in mental load for the 30+ group. So basically, when the number of options gets too high, the brain struggles to compare everything. The similar standard deviations show that people in both groups answered pretty steadily, but the slightly bigger spread in the 30+ group shows that some people were pushed harder than others.

The decision fatigue scores show the same pattern. The 10+ group had a mean of 21.83 with a standard deviation of 6.49, and the 30+ group had a mean of 30.13 with a standard deviation of 10.40. This is a 38% increase in fatigue. The bigger spread in the 30+ group suggests that some people were hit much harder, maybe because of personality differences or how much mental energy they had.

The behaviour results support this. Decision time went from about 2 to 3 minutes in the 10+ group to about 5 to 7 minutes in the 30+ group. This tells us that more choices made people think longer and work harder. Satisfaction ratings were also lower in the 30+ group, around 3 to 4 out of 5, which shows that more options did not make people happier. Heuristic use jumped from 38% to 62%, meaning people used shortcuts more once they felt overloaded.

These patterns match what the theories predict. The higher NASA TLX scores support Cognitive Load Theory, which says too many items at once push working memory past its limits. The higher decision fatigue scores support Ego Depletion Theory, which says many small decisions slowly drain mental energy. The larger spread in fatigue scores in the 30+ group suggests that things like stress levels or glucose may change how fast someone gets tired.

The behaviour results show how people try to cope. They take longer, rely on shortcuts and feel less satisfied. Shortcut use and satisfaction had a negative correlation of $r = -.41$, which means that the more shortcuts someone used, the less happy they felt with their final choice. People in the 30+ group also spent more time moving around the categories, which added even more load.

The effect sizes were large. For mental workload, $\eta^2 = .364$. For decision fatigue, $\eta^2 = .192$. These values show that choice quantity has a strong real impact. On digital platforms with endless lists, these mental costs can lead to people giving up on choosing or feeling less engaged. This challenges the idea that bigger catalogues always help users and instead supports more curated setups.

There was also a clear threshold. When the number of options went past about 10 to 15, the negative effects already started. When the number went past 30, the negatives jumped even more. This matches the well-known limits of working memory. The findings show that choice overload works through two connected processes. One is immediate overload, when too many options hit the brain all at once. The other is slow depletion, when each small choice slowly drains energy. These two processes work together and make people tired faster.

Shortcut use went up a lot in the 30+ group, showing that people simplify choices to deal with overload. But this often leads to lower satisfaction, which matches the “paradox of choice.” Longer decision times did not help either. Thinking longer actually made satisfaction worse. This means that once someone's mental limits are passed, more thinking does not improve anything.

The effect sizes from the t tests were also strong. For mental workload, Cohen's d = 1.49, and for decision fatigue, d = 0.96. These are large effects and show that these results matter in real places like online shopping, streaming, healthcare and public policy, where too many choices can lead to confusion, slower decisions or avoiding decisions altogether.

Interpretation in Relation to Hypotheses

Support for H1: High-Option Interfaces Increase Decision Fatigue

The findings give strong support for H1. Participants in the 30+ condition showed 38% higher fatigue scores, took almost twice as long to decide, and relied more on shortcuts. These patterns match what Ego Depletion Theory and choice overload research expect. The lower satisfaction reported by the 30+ group also shows how larger choice sets can lead to more regret and less confidence in the final choice

Support for H2: Shortcut Use Mitigates Fatigue (Partial Support)

H2 is only partly supported. Participants in the 30+ group used shortcuts and recommendations 63% more often, which fits the idea of satisficing. These shortcuts did reduce some effort, but they did not remove fatigue, and shortcut use was negatively related to satisfaction. This means shortcuts help people cope but do not fully protect them from the mental strain caused by large choice sets.

Support for H3: Cognitive Load Intensifies Fatigue

The results clearly support H3. NASA TLX scores were 64% higher in the 30+ condition, showing that higher cognitive load and higher fatigue occurred together. Participants also spent more time moving between categories and reported more frustration. These patterns match the Load Interaction Model, where increased mental load speeds up the onset of fatigue.

Threshold Effect and Theoretical Integration

The data point to a consistent choice overload threshold around 10–15 options. Once option sets pass this range, working memory becomes overloaded, decisions become slower, and accuracy declines. Poorly organized interfaces make this threshold lower, while cleaner and clearer layouts help raise it. The results also show two processes working at the same time: immediate cognitive overload from too many options at once, and gradual resource depletion from repeated comparisons. Together, these processes increase mistakes, shortcut use, and decision avoidance.

Practical Implications

Digital Interface Design

Limit visible choices to about 10–15 items to reduce overload.

Use clear categories and simple filters to guide users.

Use recommendation tools carefully and avoid design elements that create pressure.

Marketing and Consumer Behaviour

Curated and simplified product sets can increase satisfaction.

Very large catalogues may lower conversions because users feel stuck or overwhelmed.

Healthcare Decision-Making

Patients benefit from decision aids and clear communication when treatment options are complex.

Too many choices in medical settings can reduce understanding and lead to weaker decisions.

Policy and Regulation

Policy tools and public systems should avoid unnecessary complexity.

Clear decision tools and transparent algorithms can reduce overload and support better choices.

ETHICAL CONSIDERATIONS

This study brings up several ethical points because it deals with choice overload and mental effort. These points involve protecting participants, keeping data safe, understanding how the findings might be used and considering the wider impact of research on digital design.

Participant Protection and Informed Consent

Since large choice sets can lead to frustration and short-term mental fatigue, the study made sure participants were protected. They received clear instructions before starting, they could stop at any time and they were fully debriefed. The consent form also explained that the task might feel mentally demanding.

One challenge is that cognitive fatigue is hard to describe in advance. People do not always know what this type of mental tiredness feels like until they experience it. This brings up the question of whether standard consent forms explain this well enough. Future studies may need clearer descriptions of what cognitive load can feel like.

Data Privacy and Confidentiality

The study collected behavioural data, such as how long people hesitated, how they compared options and how tired they felt. All data were anonymized, stored securely and only accessible to the research team. Still, as behavioral data becomes more detailed, there is a growing concern that certain patterns might be linked back to individuals in the future.

To reduce this risk, only group-level findings were published, and raw data were deleted after analysis. A broader concern is how such data could be misused outside research, especially if companies used it to identify or influence people who may be more vulnerable to decision fatigue. This shows the need for updated privacy standards as this type of research becomes more advanced.

Balancing Scientific Rigor with Participant Well-Being

To test choice overload, the study exposed participants to more than 30 options. This was necessary for the research but also increased mental load. To balance this, the sessions were kept short, participants were monitored for signs of strain and rest was allowed.

A wider issue is that many students take part in several cognitive studies. Current ethics rules do not fully address the long-term effects of repeated participation in tasks that can be mentally tiring. This suggests the need for clearer guidelines about cumulative cognitive load.

Commercial Misuse and Researcher Responsibility

The findings can help improve digital platforms, but the same information could also be used in harmful ways. For example, companies could design interfaces that overwhelm users on purpose to keep them engaged. Although the intention of this research is to support healthier digital design, misuse cannot be fully prevented.

To address this, the research team worked with digital well-being groups, included warnings about manipulative design practices in the written report and shared results with a focus on ethical use. Still, this does not cover all risks. This raises the idea that behavioral research may need a “dual-use” review process similar to those used in other scientific fields.

Cultural Sensitivity and Global Implications

The study mainly involved Western participants, which limits how widely the findings can be applied. Decision-making varies across cultures. For example, earlier research shows that Indian users take 24% longer to choose even when they have fewer options. This means design guidelines based on Western samples may not fit all cultural contexts.Researchers therefore have a responsibility to explain where their findings apply and where they may not. The field also needs to consider whether current research includes enough cultural diversity or whether it unintentionally promotes Western patterns as universal.

Long-Term Societal Impacts

The findings also raise larger questions. If people face large choice environments every day, this may slowly drain their cognitive resources. This connects to wider concerns about digital overload and attention demands. If choice overload becomes a constant part of digital life, it may affect overall decision-making ability.

Researchers should think about how these results relate to digital policy, education and platform regulation. The findings raise important questions, such as whether researchers should advocate for change when evidence suggests that certain digital practices may cause cognitive strain, and how to balance scientific neutrality with the responsibility to support healthier digital environments.

Discussion

The large rise in cognitive load in the extensive-choice condition (a **63.5% increase** in NASA-TLX scores) supports what existing research says about the limits of working memory. In line with Cognitive Load Theory, participants who faced **30+ options** moved beyond what their cognitive systems could realistically handle. The repeated checking of items, hesitation and signs of decision paralysis show a clear bottleneck. This likely reflects limits in the prefrontal cortex, which is responsible for comparing information and weighing value. These limits help explain why many participants felt mentally overloaded when they had too many choices.

The results on decision fatigue also build on Ego Depletion Theory. Participants in the high-choice group reported much higher exhaustion, which shows that long and complex decision-making steadily drains mental resources. The wider spread in fatigue scores suggests that individual differences matter. Factors such as cognitive stamina, stress tolerance and decision style may make some people more affected by overload than others. In behaviour, fatigue showed up as greater shortcut use, less deep comparison and lower satisfaction, showing how mental strain can influence emotions and shape the choices people ultimately make.

One important finding is that spending more time deciding did not improve outcomes. Even though participants in the 30+ group took almost twice as long to choose, they felt less certain and more regretful. This challenges the idea that more options and more thinking led to better decisions. Instead, too many options seem to increase worry about making the wrong choice. The heavier use of heuristics, while helpful in reducing effort, likely pushed participants toward choices that felt “good enough” rather than truly satisfying.

These results have practical value. In consumer settings, curated product selections may lead to better decisions and higher satisfaction than large catalogues with little structure. In workplaces, breaking complex decisions into smaller steps and including short cognitive breaks may help prevent a drop in judgment quality. The strong increase in shortcut use under high-choice conditions also suggests that decisions made later in long evaluation tasks may be less accurate.

The findings also raise concerns for digital platform design. Features such as infinite scroll, large grids of items and expanding content libraries may unintentionally create constant choice overload. Tools like progressive disclosure, clear filtering systems and recommendation features focused on clarity (rather than pressure) can help reduce cognitive strain while still preserving user freedom. Designing digital environments with cognitive limits in mind may lead to more satisfying user experiences.

There are several directions for future work. More research is needed on individual differences in susceptibility to overload, which could help identify who is most at risk. Developing and testing decision-support tools is another promising direction. Cross-cultural work could show how different societies experience and manage choice. Neuroscientific methods such as fMRI and EEG could give deeper insight into the brain processes involved in overload and fatigue.

Overall, this study shows that the number of available options has strong cognitive, emotional and behavioral effects. The large changes across multiple measures confirm that choice overload is a real psychological challenge with clear consequences. These findings question the idea that more choice always helps users and show that effective decision environments should balance variety with what people can realistically manage.

Conclusion

This dissertation examined decision fatigue in digital spaces, especially on streaming platforms and food delivery apps, where people face many small decisions every day. The study used a mixed-methods design to deal with major gaps in past research, such as the lack of causal tests and the limited focus on everyday digital decisions that add up over time. By combining controlled experiments with qualitative responses, the study gives a clearer picture of how large choice sets affect mental effort, emotions and behaviour. It also offers guidance for more thoughtful and user-cantered digital design.

The results strongly supported the main hypothesis: larger choice sets directly increase decision fatigue and cognitive load. Participants who saw 30+ options had much higher NASA-TLX and Decision Fatigue Scale scores than those who saw 10+. The effect sizes were large enough to show that this is not just a small difference but something with real practical impact. These results fit with Cognitive Load Theory, since working memory becomes strained when too many options must be compared, and with Ego Depletion Theory, since repeated decisions gradually drain mental resources. Together, the findings point to a clear cognitive limit that digital platforms should not exceed.

The qualitative answers added important context. Participants in the high-choice condition often described frustration, uncertainty and trouble keeping focus. Many relied on shortcuts to make the decision easier, but these shortcuts often led to lower satisfaction and weaker choices. This supports the idea that “more choice” does not always lead to better decisions. Several participants said that taking longer to decide did not help them choose more effectively. Instead, longer effort increased their fatigue and made the experience feel worse.

By combining both datasets, the study shows that choice overload works through two main processes at the same time. One is the immediate strain that comes from having too many items on the screen. The other is the slow build-up of fatigue from making several small decisions in a row. This mixed-methods approach helped identify not only the outcomes but also the internal processes that shape them.

The findings carry practical value across different fields. For digital design, the results show the need to reduce unnecessary options, create clearer layouts and use recommendation systems in ways that support users rather than overwhelm them. For marketing, the results challenge the idea that more choices create better experiences. Smaller and clearer product sets may lead to higher satisfaction. In healthcare, simplifying treatment options and improving communication could help patients make better choices and feel less stressed. More broadly, the study contributes to decision-making theory by refining current models and suggesting a possible threshold beyond which additional choices reduce decision quality.

This dissertation also recognizes its limitations. The simulated interfaces allowed for controlled testing, but they do not fully match the complexity of real platforms. The sample was diverse but not globally representative, and self-report measures always carry some subjectivity. These limitations point to several useful directions for future work.

Future Research Directions

Future research can increase realism by using real-world datasets, eye-tracking and physiological measures. It can explore neural activity with tools like EEG or fMRI to understand how overload develops in the brain. Individual differences—such as personality, motivation, cognitive capacity and decision styles—also deserve closer attention. Cross-cultural studies are needed to understand how cultural values shape tolerance for choice. Long-term studies could show how repeated exposure to high-choice environments affects people over time. More work is also needed on interventions, including simplified interfaces, decision aids and progressive disclosure. Another important direction is examining how AI both reduces and increases overload through personalization. Studies should also look at how decision fatigue spreads across daily apps. Finally, research can support the development of adaptive interfaces and explore policy questions about transparency and user protection.

In conclusion, this dissertation provides strong evidence that too much digital choice creates really mental and emotional costs. Recognizing these limits is important for designing platforms that support users instead of exhausting them. The results encourage a shift away from the idea that “more is always better” and toward design approaches that balance flexibility with what people can realistically process. Moving in this direction will require collaboration among researchers, designers, policymakers and industry leaders. By combining ethical awareness with human-cantered design, digital systems can become more supportive, helping users make decisions in a healthier and more sustainable way.

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