LUISS

DEPARTMENT OF MANAGEMENT

Chair Advance Marketing Management

The Illusion of Choice, Investigating Algorithmic Transparency, Personalization, and User Empowerment

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Abstract

Algorithms no longer merely predict our preferences they structure our choices, define our horizons, and increasingly mediate the experience of being a decision-maker. In this shifting digital ecology, where personalization is omnipresent and algorithmic logic becomes infrastructural, this thesis asks a deceptively simple question: *do recommender systems empower users or quietly appropriate their agency?*

Bridging psychological theory and marketing science, the study constructs a nuanced framework of algorithmic empowerment. Drawing on Self-Determination Theory, the concept of Digital Locus of Control, and recent breakthroughs in consumer AI research, it explores how algorithm type (generalized vs. specialized) influences users' perceived empowerment. A moderated mediation model (PROCESS model 83) hypothesizes that perceived autonomy and perceived transparency mediate this relationship, while DLOC moderates the effects by shaping how users internalize algorithmic behaviours.

An experimental design with 298 participants manipulates algorithm framing across hedonic and utilitarian contexts. Results reveal that empowerment is not embedded in the system itself, but emerges from a dynamic interplay between perception, expectation, and control. Specialized systems enhance relevance but risk overfitting; generalized ones promote discovery but may dilute intention. Empowerment surfaces when users understand and negotiate the algorithmic process not simply when content is optimized.

This thesis reframes recommender systems as psychological environments, not just technological artifacts. It argues that meaningful agency in algorithmic spaces depends less on what systems do, and more on how they are perceived, interpreted, and resisted. In doing so, it advances a theory of algorithmic empowerment that is both empirically grounded and ethically urgent proposing not better predictions, but more conscious participation in the architectures that shape us.

Introduction

Algorithms are increasingly mediating not just the availability of information but also the very infrastructure of consumer agency. In environments designed according to behavioural predictions, individuals are no longer the sole designers of their choices; instead, they are co-navigators in systems that anticipate, nudge, and even pre-empt their desires. Recommender systems are a case in point shifting from simply making recommendations to actively influencing decision pathways raising fundamental questions about whether personalization actually empowers users or merely creates an illusion of agency.

In this research, empowerment is framed not by technological innovation but by people's own perceptions of mastery, autonomy, and competence. Employing Self-Determination Theory (Deci & Ryan, 1985) and corresponding research in organizational psychology (Spreitzer, 1995), this thesis examines what impact algorithmic design has on these underlying principles. However, progress only comes about through combining these two perspectives, those of psychological theory and the field of marketing.

Current studies in the Journal of Marketing and Journal of Marketing Research have shown the significant impact of algorithmic framing and domain context on users' emotional and behavioural responses. Cian and Krishna (2020), for instance, have described how algorithmic influence differs significantly between utilitarian and hedonic domains, where users are more likely to consider AI-recommended offerings as more legitimate and reputable when performing goal-seeking tasks. The finding has directly guided product segmentation in the thesis in order to study empowerment effects unique for different domains.

Similarly, the notion of algorithmic transference through which perceptions about AI reliability in one situation are transferred to others, as shown by Cian and Krishna (2022) shows that empowerment is not just an output of the system but a function of cognitive and affective influences. The body of literature has provided both theory and empirical evidence for incorporating Digital Locus of Control (DLOC) as a moderating variable within theory. It is individual differences in cognitive tendencies that ultimately determine perceptions of transparency as empowering or patronizing and acceptance or aversion to personalization.

The relevance of autonomy and perceived transparency as psychological mechanisms is also supported by studies in the context of marketing. In an article in the Journal of Marketing Research, Tucker (2014) showed that privacy expectations of users interact with personalization attempts to influence feelings of control, highlighting that empowerment is created not only by explainability but by its congruence with user beliefs. These findings align with the approach of the present thesis in considering not only the structural features of systems, but how these features are perceived and psychologically processed.

In its final conclusions, this research departs from simplistic descriptions of recommender systems as either efficient or manipulative. Utilizing a moderated mediation framework, it accepts that algorithmic influence acts through sophisticated psychological processes that are shaped by both system design and user inclination. The structure of the model, including algorithm type categorization, perceived transparency, perceived autonomy, DLOC, and empowerment, is an integration of consumer scholarship, marketing ethics, and behavioural science and responds directly to recent pleas in Marketing Science for models linking algorithmic effectiveness to user-centric results.

In alignment with previous academic studies, empowerment has shifted from being a unidimensional conceptual framework to being an measurable, variable outcome based primarily in psychological factors, including perceptions, trust, and internalization of algorithmic mediation on behalf of users. Through research in this vein, the thesis not only extends previous marketing research but also enters previously untouched areas: those psychological processes underpinning algorithmic empowerment.

Chapter 1 – Literature review

1.1 Theoretical Foundations of Empowerment

Empowerment is a multifaceted concept that has been discussed within a number of disciplines, ranging from political science and psychology to education, and information technology. Empowerment has its origins within sociopolitical movements aimed at both individual and group autonomy. Early empowerment theories concentrated on the redistribution of power to marginalized groups, active engagement, and improving people's abilities to challenge systemic arrangements. Freire (1970) coined the term “conscientização”, with a point that people become empowered by enhanced critical consciousness and active engagement with the process of transforming their situation. This thinking became a key building block for participatory pedagogies and social justice movements and later influenced subsequent interpretations of empowerment both as a process and a product.

As discussions around empowerment developed, its application widened from predominantly social and political orientations to include psychological dimensions. Rappaport (1987) defined empowerment as a multifaceted phenomenon that occurs at individual, organizational, and communal levels. Rappaport linked empowerment with cognitive self-awareness, proactive involvement, and collaborative decision-making processes.

Of specific concern, Zimmerman (1995) outlined a psychological empowerment framework with three main dimensions: intrapersonal (self-efficacy and perceived competency), interactional (recognition and insight regarding power relations), and behavioural (participation in decision-making processes). His work emphatically stressed that empowerment is not the mere navigation of barriers but involves the impartation of a sense of mastery that people exercise over themselves and, at the same time, creating a need to improve their environment.

At the same time, Bandura (1986) provided the psychological foundations of empowerment using his theory of self-efficacy, which asserts that a belief in one's own ability to be able to accomplish things has a direct bearing on people's motivations and choice-making processes. This is particularly applicable within the context of virtual

spaces, where a sense of control may affect the extent of activity on computers, for example, on websites that provide recommendations. Those who feel that they have the control to dictate and know algorithmic recommendations are likely to feel a sense of empowerment.

The concept of empowerment has been integrated into Deci and Ryan's self-determination theory (SDT, 1985), which argues that human motivation is shaped by three innate psychological needs: autonomy, competence, and relatedness. The extent to which each of these needs is satisfied impacts people's overall well-being and their level of engagement. In algorithmic environments, SDT provides a framework for determining whether software systems support or hinder user empowerment. When algorithms provide meaningful choices, allow customization, and build confidence in decision-making, they support the tenets of SDT and thus positively reinforce user autonomy.

In contrast, opaque recommendation mechanisms that limit options or reduce the user's agency may promote disengagement or result in more passive content consumption.

Recent research by Mazzù et al. (2022) reinforces this perspective by demonstrating that perceived usefulness and ease of use significantly enhance user acceptance and feelings of control in digital decision environments, two components that directly contribute to psychological empowerment.

In modern-day digital realms, the notion of empowerment has changed with the development of artificial intelligence and algorithmic choice systems. Zuboff (2019) discusses how digitized platforms increasingly shape human agency, arguing that AI-driven recommendations systems often prioritize consumer interaction and business interests at the expense of individual autonomy. Similarly, Noble (2018) discusses the effects of algorithmic bias on the entrenchment of pre-existing structural inequalities and raises questions on the true empowerment of consumers when they engage online and their actions are directed by opaque algorithms with a profit motive.

Rising reliance on artificial intelligence-driven recommendation systems highlights the need for examining empowerment within algorithmic mediation contexts. While some scholars argue that carefully designed recommender systems could optimize autonomy by presenting relevant and precisely designed content, other scholars have warned that

over-curation by algorithms could lead to filter bubbles, decreased diversity, and cognitive rigidity. Burr and Cristianini (2019) explain the paradox that while individualization may create efficiency, it at the same time erodes the capability of the user to engage with unstructured material.

1.2 Foundations of Recommendation Systems

Recommendation software is a core element of online sites and has become a decisive determinant of consumer choice across e-commerce, streaming sites, and social networks. These programs utilize machine learning and artificial intelligence methods to analyse consumers' preference patterns and generate individualized recommendations. Ricci, Rokach, and Shapira (2015) outline models for recommendations extensively and cover collaborative filtering, content-based filtering, and hybrid models that combine several methods to improve accuracy and relevance.

Collaborative filtering bases recommendations on the collective actions of consumers to create recommendations, while content-based filtering relies on items' properties to match consumers with related material. Hybrid models blend the two methods to maximize customization and overcome limitations of the two methods, which involve sparsity of data and the cold-start problem.

Advances in deep learning and reinforcement learning have had a profound effect on the evolution of recommender systems, making it possible to design dynamic models that adjust their recommendations based on real-time usage interactions. Covington, Adams, and Sargin (2016) demonstrate the way deep neural networks improve content recommendations on sites like YouTube, with algorithms adjusting rankings of content based on different levels of engagement from the user base. Similarly, Zhang et al. (2019) explore reinforcement learning methods that optimize recommendations by continually incorporating user feedback to improve the accuracy and diversity of proposed items.

Baccelloni (2022) explores how recommendation agents can create implicit social networks, significantly influencing users' decision-making processes. His research highlights the dual role of these agents in both facilitating personalized recommendations and shaping user behaviours through algorithmic specialization.

While these advancements dramatically increased the effectiveness of recommendation systems, they simultaneously have raised issues about the concentrating of the power that is involved with algorithmic choice-making.

1.3 The Influence of Recommender Systems on User Autonomy

Recommender systems play a dual role in both enhancing and constraining user autonomy. On the one hand, they facilitate access to personalized content and reduce the daunting nature of information, and on the other, they shape users' decision-making processes in subtle ways. Sunstein and Thaler (2008) discuss the concept of algorithmic nudging, where systems nudge users towards specific content choices without overt coercive interventions. This raises questions about the genuineness of users' autonomous decision-making versus their possible manipulation by algorithmic optimization techniques geared towards user engagement maximization.

Substantial academic research has been carried out on how systems affect the decision-making processes of their users. Burr and Cristianini (2019) argue that recommendation systems present an illusion of autonomy to the users, who feel they are being presented with highly individualized recommendations, even when their actual choice is based on the underlying algorithmic designs. Zuboff (2019) takes a step further from that critique by analysing the phenomenon of surveillance capitalism, where online platforms take leverage on people's interaction using algorithms and monetize their information, thus diluting genuine autonomy.

Empirical studies show that recommender systems can also promote passive decision-making habits. Benjamin, Berger, and Biswas (2020) demonstrate how overdependence on algorithmic curation can discourage users from exploring a variety of content choices, thus reinforcing their cognitive dependence on algorithm-driven choices. This phenomenon is consistent with Skinner's (1953) theory of operant conditioning, where users are conditioned to rely on the choices provided by the system through reinforcement mechanisms such as instant gratification and curated information cycles.

Despite these concerns, studies show that well-designed recommender systems have the potential to enhance user autonomy when they incorporate transparency and user control

mechanisms. Helberger et al. (2020) posit that the best way platforms can ensure that user autonomy is maintained is through the adoption of interactive preference changes that allow users to change recommendations in real-time. Further, Zhang and Chen (2020) argue that features that facilitate explainability, like explaining the reason why recommendations are made, improve users' perception of agency, enabling them to make better-informed choices.

However, the existing literature does not fully examine the effects of different levels of algorithmic transparency on users' long-term autonomy. While increased transparency can promote trust, it does not necessarily guarantee an increased sense of control, as users lack sufficient knowledge to interpret and use algorithmic explanations effectively. Future research must address the effects of algorithmic nudging and dependence on choices on users' abilities to make informed and autonomous decisions, so that recommender systems do not undermine digital autonomy in their attempts to promote user engagement.

Recommender systems play a double role by both facilitating and constraining users' autonomy. On the one hand, they facilitate access to personalized content while mitigating the difficulties that come with information overload; on the other, they shape the decision-making processes of users in subtle ways. Sunstein and Thaler (2008) discuss the idea of algorithmic nudging, in which systems steer users towards specific content choices without overt coercion. This raises questions about the autonomy of users' independent choice-making with respect to the possibility of subtle manipulation by algorithmic techniques designed to maximize engagement.

1.4 Algorithmic Mediation and the Ethics of Empowerment

Algorithmic recommenders are primarily aimed at enhancing personalization and customer experience. Yet, they produce unforeseen issues limiting users' control. Additional evidence indicates that difficulties such as algorithmic prejudice, transparency, and obscure decision-making hinder users' capability to grasp, challenge, or alter the provided recommendations. For instance, Noble (2018) and Baeza-Yates (2018) clarify that algorithmic answers tend to reproduce and perpetuate the societal disparities realized in data and systems. These issues can form power imbalances among

platforms and users, particularly where individuals tend to receive content suitable for popular narratives or past behaviours.

Filter bubbles are an example of this circumstance. These occur when algorithms recommend to users that they already prefer and restrict their opportunities to encounter alternative views (Pariser, 2011). Cinelli et al. (2021) demonstrate the restriction of information can enhance variation in beliefs and make individuals more closed-minded, particularly on the social media and engagement-oriented sites. Filter bubbles impair critical thinking in users when it comes to empowering them because they are subtly discouraged from seeking out information and rely more on the information systems provide them.

Ethical issues worsen due to trickery which is aimed at attracting more money or attention rather than that which is good for users. Zuboff's (2019) conception of surveillance capital demonstrates how certain platforms exploit information about things people do in order to alter their behaviours, removing their power to make choices. Where personalization can mask an even larger behaviour-changing effect, there are significant questions around whether these individuals are ever making choices for themselves.

Researchers have proposed various means of making users feel more in control. For their part, Nguyen et al. (2014) propose the use of various algorithms that alter content so filtering effects are minimized yet users are kept engaged. Like them, Helberger et al. (2020) emphasize that allowing users to customize recommendation settings so they have control over which content they view and regain control over their learning is essential. Implementing these solutions at scale is challenging with systems created for productivity and retaining users and not being open or empowering.

These are indications we must comprehend user-centred algorithmic mediation ethically. Rather than assuming personalization is always best because it makes users make their own choices, studies now are prompting us to take a keen look at just how recommendation systems are tied to the things people enjoy and how they perceive them, this is an issue with which this thesis engages.

1.5 Transparency, Explainability, and User Control

Transparency, or how far users are able to view and manage recommendation procedures, is arguably the single most significant determinant of empowerment within algorithmic environments. Pasquale (2015) argues against the rise of "black box" AI, in which obscure decision-making mechanisms limit user agency. A lack of transparency within recommender systems is of concern regarding trust, accountability, and user control since users cannot necessarily know the full extent of how their online experiences are being managed.

Explainability in AI (XAI) is a response to these concerns, aiming to enhance user understanding of algorithmic behaviours. Zhang and Chen (2020) note that transparency in AI recommendation systems enhances trust and enhances user engagement. According to research, when users receive explanations for the reasons why certain content is recommended, they experience higher confidence levels in decision-making and a perception of control. However, experienced control is additionally determined by both the user's privacy expectations as well as his or her data usage sensitivity where personalization, for instance, is founded upon behavioural monitoring (Tucker, 2014). In the latter scenario, transparency must complement good privacy control to avoid generating resistance or withdrawal.

User control mechanisms emerge as a major means of mediating empowerment and personalization. Some methods for offering additional user control in recommender systems are outlined by Tintarev and Masthoff (2012) including explicit feedback loops, interactive filtering, and dynamic recommendation criteria. User control mechanisms allow users to enable them to alter their content visibility to prevent heavy reliance on automated recommendations. Balog et al. (2019) suggest the use of human-in-the-loop systems to involve users directly in the process of improving their recommendations to personalize it based on their evolving preferences.

Despite progress in explainability and user control, there remain knowledge gaps regarding the effects of different levels of explainability on long-term user control. A study by Eslami et al. (2018) indicates that while explainability features can enhance initial trust, their effect on long-term use and user empowerment is contingent on the demographics of the users.

Future work must investigate how explainability models, specific to the user's personal level of knowledge and preference, can optimally maximize algorithmic performance and user control. Resolving these challenges will be critical in designing recommender systems that empower, rather than limit, users' decision-making.

1.6 Generalized vs. Specialized Recommender Systems: Which Model Enhances User Empowerment?

An increasingly important, yet still under researched, area in the field of recommender systems research involves the differential psychological effects of generalized and specialized algorithmic systems.

While the technical literature has long weighed the trade-offs between scope and precision, the implications of these variables for user empowerment, defined here as the subjective sense of agency, control, and competence in online decision-making, remain to be adequately examined.

Generalized recommenders are mostly built into serving large user populations with behavioural data sourced from diverse populations. Therefore, they often present the users with a broad range of content, known as algorithmic serendipity as described by Sunstein (2018). For users, the serendipity can have the ability to initiate exploration and address the issues of echo chambers, hence enabling autonomy through unexpected discovery. However, the very same mechanism can, alternatively, produce situations where the overabundance of imprecise targeted recommendations causes decision fatigue or abandonment (Iyengar & Lepper, 2000; Schwartz, 2004). In such situations, the users are likely to surrender more control over decision-making processes to the algorithm, which weakens their sense of agency, especially when default options seem cognitively easier to accept compared to active exploration.

In contrast, specialized algorithms are deliberately developed to improve relevance through closely linking suggestions with users' past behaviours, intent, and contextual data. Such improvement of prediction often builds higher satisfaction among users and increases perceived trustworthiness of the system (Adomavicius & Tuzhilin, 2005), consistent with personalization and design principles that are user centred. However,

these systems also carry certain risks. Jannach and Adomavicius (2016) warn against overfitting, where users are always led to familiar or validating content. Over time, this can cause cognitive confinement, hence limiting exposure to diverse perspectives and discouraging active use of content. For an empowerment perspective, this constraint of choice can reduce the perception of the user as an intelligent producer and decrease perceived autonomy, even when suggested content is perceived to be very relevant.

The balance between autonomy and efficacy is very significant psychologically. Even though systems that generalize have the potential for increased diversity and exploratory learning, this is achieved at the cost of personal utility and trust among users. Specialist systems can increase satisfaction among users, but they do this at the risk of enabling algorithmic dependency with the system as gatekeeper, and not simply as an enabler of meaningful decision. As Burr and Cristianini (2019) note, there is an irony here: the more accurate the algorithms are at predicting individualized choices preferred by users, the more these choices may not seem to embody autonomy.

The present study empirically examines the tension through the analysis of users' experiences of empowerment in generalized and specialized systems. By manipulating the type of algorithm in an experimental design, the study seeks to identify which model best satisfies the basic psychological needs of autonomy, competence, and relatedness, as outlined by Self-Determination Theory (Deci & Ryan, 1985). In doing so, the research addresses a comparatively overlooked dimension of current research: to what degree do ubiquitous examples of algorithmic personalization affect user control, and do these effects occur negatively, thus limiting choices to a point of predictability?

1.7 Individual Dispositions and the Role of Digital Locus of Control

Whereas much of the available research with relevance to algorithmic empowerment focuses on system-level factors, like transparency, personalization, or control. There is growing scholarship devoted to the individual differences in perception and understanding of these traits. A critical variable often underemphasized is the Digital Locus of Control (DLOC), which addresses the extent to which users feel that they can shape outcomes in interactive environments.

The theoretical basis of this model draws upon Rotter's (1966) broad theory of locus of control, which makes the distinction between an internal orientation in which individuals see control as arising from their own behaviours, and an external orientation, in which control is seen in terms of factors outside the individual. This differentiation is important when attempting to understand perceptions of agency in interactive environments.

People with a high internal locus of control (DLOC) tend to interact actively with algorithmic systems, have a high tendency to consider tailored cues seriously, and speak about controlling recommendation systems. People with an external DLOC tend to view these systems as mysterious or intimidating, which can end with withdrawal or passiveness tendencies (Chandler & Schwarz, 2010; Zuckerman et al., 2019). These dispositions dictate people's responses towards design elements meant to increase their empowerment.

The DLOC's moderating function is especially relevant when investigating the mediated relationship between algorithmic architecture and empowerment. Empirical research suggests that dimensions like transparency and autonomy have very little direct psychological effects when considered independently but, rather, have their effects mediated through users' perceived control. For example, an extremely transparent recommendation algorithm can fail to have an empowering outcome if the user does not trust their own ability or right to decode and react to them. For this reason, DLOC plays a gatekeeping function, amplifying or weakening the effectiveness of efforts towards empowerment at the psychological level.

The identification of DLOC as a moderating variable refocuses attention from expected outcomes generated through the system towards experience adapted to the person. This viewpoint is endorsed by theory perspectives regarding human-computer interactions, which emphasize the coactive nature of agency among the person and the system (Sundar & Marathe, 2010), which is why there is called for an empowerment reassessment that is contingent upon context, not absolute. In the theory of recommender systems, this would mean that empowerment does not originate from algorithmic execution alone but from active participation of the person in the mediation, which is shaped through prior beliefs, expectation, and control perceptions.

1.8 Theoretical Gaps, Individual Differences, and the Research Model

Despite the growing sophistication of algorithmic recommendation systems, there remain robust theoretical and empirical gaps in the understanding of their long-term impacts on the psychological well-being of users, including their sense of empowerment. Although earlier empirical work predominantly centred around variables such as user satisfaction, trust, and usage (e.g., Shani & Gunawardana, 2011; Knijnenburg et al., 2012), there have been few investigations of how the very characteristics inherent to algorithms, particularly transparency and the extent of personalization, impinge upon users' perceived agency and autonomy (Ajzen, 1991; Sundar, 2008). These are integral parts of the theory of empowerment as expressed in organizational contexts (Spreitzer, 1995) as well as in virtual spaces (Lomborg & Frandsen, 2016), where users take not just passive roles but active roles in participatory sense-making.

One of the main limits lies in the interactive relationships between transparency, personalization, and autonomy. Whilst transparency can potentially increase trust and perceived legitimacy of a system (Tintarev & Masthoff, 2015), how much it can truly support empowerment is still controversial. Eslami et al. (2018) caution that transparency can seem superficial or even manipulative, depending on the inability of users to take action when provided with information. Similarly, whilst specialized algorithms often increase perceived relevance of content, they inevitably risk creating algorithmic lock-in (Andrejevic, 2013) and compromising user agency through predictable behaviours.

In addition, while past research has highlighted the benefits of personalization in reducing cognitive overload and maximizing user satisfaction, Burr and Cristianini's (2019) study also highlights the potential dangers of passive content consumption, where users follow the suggestions of systems without critical evaluation. This leaves relevant questions about the degree to which personalization supports independent decision-making or quietly undermines it with the ongoing conditioning of the behaviours of users. The long-term psychological impacts of such mechanisms are under researched.

Another relatively under researched area concerns the efficacy of interactive control features, like adapted recommendation filters or real-time feedback options, on creating feelings of empowerment. Even though these tools are aimed at augmenting the experience of agency, they rely considerably upon the user's competence with algorithmic

systems and the extent of their digital literacy (Helberger et al., 2020). This means that one-size-fits-all solutions do not always have consistent outcomes, hence the need for cognitive and psychological factors to also be taken into account in personalization.

Recent empirical research highlights the significance of individual differences as systematic moderators in the empowerment model. Specifically, the theory of Digital Locus of Control (DLOC), an extension of Rotter's (1966) original theory, offers a salient framework for explaining the differences seen among users. Those with an internal DLOC are likely to hold the view that they have the power to shape online occurrences, value personalization, and use algorithmic mediation with an evaluated use pattern (Chandler & Schwarz, 2010; Zuckerman et al., 2019). Those with an external locus are likely to see these suggestions as set in place or outside of their control, which may cause them to back away or experience learned helplessness. These actions have notable ramifications for the effectiveness of transparency and control strategies: where users do not have trust in their power to make an impact or make sense of the system, even the best-crafted interfaces are inevitably likely to fail to produce empowering outcomes.

Finally, users' responses to algorithmic personalization vary depending upon certain contextual factors. The unique application domain, specifically hedonic versus utilitarian product categorizations, can influence the saliency of autonomy and transparency in users' perceptions. Hedonic decisions, often driven by emotional engagement, may increase users' sensitivity to perceived agency; in contrast, utilitarian contexts are likely to elicit more pragmatic and cognitively bounded responses (Dhar & Wertenbroch, 2000). These differences across different application areas further complicate the empowerment task and point towards the need for an overarching model that accommodates factors at the system, individual-user, and contextual levels.

Given these limitations, we put forward an overall explanatory framework that combines systemic architecture and individual disposition to predict perceived empowerment. Specifically, we argue that:

H1. Perceived transparency and autonomy enhance the perception of empowerment.

H2. The specialized algorithms show substantially higher levels of empowerment compared to the generalized ones;

H3. The locus of control in the digital realm acts as a mediator of the relationship of algorithm type with transparency and perceived autonomy; the more internal locus group perceives higher algorithm type influence.

H4. The type's effect on empowerment is dependent upon the product category, with hedonic and utilitarian products separating into different categories.

Chapter 2 – Methods

2.1 Research Design and Methodology

This chapter outlines the methodological framework utilized to examine the impact of algorithmic design choices upon individuals' experiences of psychological empowerment in virtual spaces. The research seeks more particularly to examine the mediating roles of perceived transparency and perceived autonomy in the association between different types of recommender systems and user empowerment, and how an individual's Digital Locus of Control (DLOC) modulates this relationship. The study utilizes a hypothetico-deductive methodological framework, based upon empirically proven theories from Psychology and Human-Computer Interaction, with the aim of generating results that are both generalizable and replicatable in the realm of human-algorithmic interaction.

The study utilizes an experimental quantitative design that is marked by a between-subjects experiment with a 2x2 factorial manipulation of two independent variables: (1) algorithm type (specialized vs. generalized) and (2) perceived agency level (high vs. low). The independent variables were manipulated systematically through manipulations of language use in an experimental environment involving an AI-powered recommendation scenario.

Participants were randomly assigned into one out of four unique experimental conditions to have an equal number of observations under each condition to avoid assignment bias to the best possible extent. The stimuli were carefully crafted to mimic real-world interactions with computerized recommender systems and address concerns over content

bias. Ecological validity in the study was improved with the addition of an initial phase where participants selected between two product categories, hedonic or utilitarian, facilitating customization of the scenario to best represent an everyday decision scenario.

The conditions were described as brief and unbiased summaries of an online recommendation system, with manipulated features infused into the text. The high and low agency conditions were contrasted depending on the degree to which the system seemed to grant the user control, whereas generalized and specialized conditions were contrasted with regards to the specificity of description regarding the algorithmic motivation.

All the other dimensions of the text, length and layout were standardized meticulously for internal validity, with the exception of these two manipulated variables. Following the scenario, the participants completed a product decision task requiring them to decide about which of two suggested products to choose, each being presented visually and described textually. This task further incorporated the algorithmic environment and supported decision processes typical of real recommender systems.

After they finished selecting their product, respondents were exposed to the survey phase of the study, where they answered a set of Likert-scale statements tasked with measuring the targeted constructs. Perceived transparency was measured with three adapted items from the study of Zhang and Chen (2020), which asked respondents questions about the extent to which they felt they understood the operational mechanisms of the system.

Perceived autonomy was measured with three adapted items from Deci and Ryan's Self-Determination Theory (1985), which measured users' feelings of freedom when in the decision-making process.

Empowerment, as a multi-dimensional construct representing confidence, agency, and psychological engagement, was measured with three adapted items from Spreitzer's works (1995) and Lomborg and Frandsen's works (2016).

The Digital Locus of Control was measured with four adapted items from the study of Chandler and Schwarz (2010), two of which were reverse scored to measure an external orientation.

All items were measured with a 5-point scale with response options ranging from 1 (strongly disagree) to 5 (strongly agree). Additional demographic and control variables collected also included gender, age, education, and digital literacy.

Construct	Number of Items	Scale Type
Perceived Transparency	3	Likert 1–5
Perceived Autonomy	3	Likert 1–5
Empowerment	3	Likert 1–5
Digital Locus of Control	4	Likert 1–5 (2 reverse)
Demographics	3	Multiple choice

Table 2.1: Overview of Measured Constructs and Response Formats in the Survey Instrument; Source: Author elaborated and AI refined based on R results.

298 participants were recruited altogether through different online channels, which included university mailing lists, discipline-related websites, and social media groups. Both convenience sampling and snowball sampling were utilized as the sampling method, with the intention of recruiting participants who had at least an elementary grasp of algorithmic systems. Participants included undergraduate, postgraduate, and early professional individuals, who aged between 20 and 35 years, which represents the demographic pattern of individuals who use recommender systems in frequently visited online spaces.

Before answering the survey, each participant needed to sign an informed consent form, and the research complied with the ethical principles outlined by LUISS University, and with the provisions of the General Data Protection Regulation (GDPR). No personal data were collected.

The data preprocessing stage included several procedures aimed at ensuring the validity of the data. First, incomplete submissions and those with abnormally short completion times were removed from the analysis. Next, responses showing a tendency to straight-line were removed. In the third step, reverse-coded items were recalibrated, and the reliability of the scales was checked with Cronbach's alpha; all constructs showed acceptable internal consistency ($\alpha \geq .70$). After this validation, composite indices for each variable were computed by averaging the respective items.

To make the analytical results easier to interpret, variables involved in interaction effect namely, algorithm type and DLOC were mean-centred, thus decreasing multicollinearity and making it easier to interpret within moderation models.

The analytical framework comprised two discrete temporal time frames. A series of linear regression models were first utilized to explore direct relationships set out in hypotheses H1 and H2, namely, the predictive value of perceived transparency and autonomy in terms of empowerment and, in addition, the effect of algorithm type.

Next, moderated mediation model analysis was conducted with the use of PROCESS Model 83 (Hayes, 2018), allowing for the indirect examination of several mediators and one single moderator. This methodology served to assess, in the first place, if DLOC operated as a moderating variable for the relationship between algorithm type and mediators (perceived autonomy, transparency), and, subsequently, if these mediators influenced empowerment (H3).

In addition, one further conditional process analysis was conducted to check if the full mediation model differed depending upon product category selected for use (hedonic or utilitarian), testing henceforth hypothesis H4. All indirect as well as all interaction effects were examined under strict scrutiny with the use of bootstrap resampling (5,000 samples), so that robust 95% confidence intervals can be obtained.

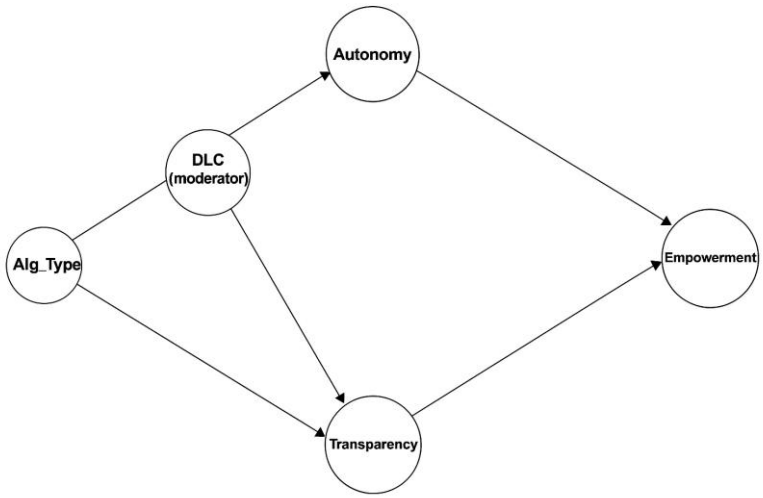

Figure 2.1: Conceptual Model of Algorithmic Empowerment (PROCESS Model 83); Source: Author elaborated and AI refined.

All statistical analyses were conducted in RStudio using efficient packages including psych for validity of scales, car for regression diagnostics, and Lavaan for structural equation modelling. Materials and code scripts were version-controlled and kept safely. Out of commitment to total replicability, the data set in its entirety and annotated R code can be released on request in adherence to best open science practice. From stimulus generation through statistical estimation of effect size, every step in this research was formulated in reference to theory predictions and methodological accuracy.

Chapter 3 – Results

3.1 Validation of Constructs and Psychometric Properties

Before analyzing the research hypotheses, the measurement tools underwent validation to ensure consistency in their evaluation of the psychological constructs under study. An Exploratory Factor Analysis (EFA) of 13 items was conducted on perceived autonomy, perceived transparency, empowerment, and digital locus of control (DLOC). The Kaiser-Meyer-Olkin (KMO) measure reported an adequate level of sampling adequacy (KMO = 0.79), with the four factors extracted explaining more than 70% of the total variance. All 13 items clearly related to their respective construct, thus establishing factorial validity. Reliability was assessed using Cronbach's alpha. Empowerment ($\alpha = 0.79$), autonomy ($\alpha = 0.77$), and transparency ($\alpha = 0.69$) exhibited satisfactory internal consistency.

The DLOC scale presented a lower alpha ($\alpha = 0.61$), primarily due to two reverse-coded items that slightly reduced internal coherence. Nonetheless, item-total correlations remained acceptable, and the scale retained theoretical robustness. Given the construct's emerging nature in digital psychology, this reliability was deemed adequate for exploratory purposes.

Descriptive statistics in addition to distributions were evaluated to determine if the data were suitable for parametric analysis. All the variables' skewness and kurtosis were within the ±1 range, indicating a good approximation toward normality.

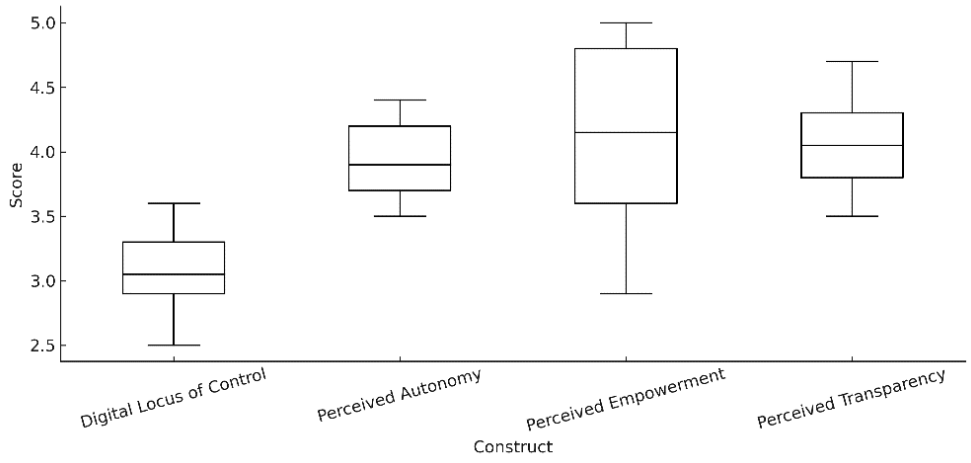

Figure 3.1 – Distribution of Psychological Constructs; Source: Author elaborated with R results.

Figure 3.1 (Boxplots of the psychological variables) is a graphical representation of the entire set of constructs, portraying the central point along with the variability of autonomy, transparency, empowerment, and DLOC ratings across the entire sample. Table 3.1 (Constructs, Items, and Measurement Scales) provides a detailed explanation of the operationalization of each construct, including the number of items, the measurement scale used, and sample items

Construct	No. of Items	Sample Item	Scale Type
Perceived Autonomy	4	I felt free to decide what I wanted to see.	5-point Likert
Perceived Transparency	3	I could understand how the suggestions were generated.	5-point Likert
Empowerment	4	I felt in control while using the platform.	5-point Likert
Digital Locus of Control	4	The algorithm determines what I do online. (reverse)	5-point Likert

Table 3.1 (*Constructs, Items, and Measurement Scales*).

These results confirm that the constructs are psychometrically sound and appropriate for subsequent inferential testing.

3.2 Descriptive Statistics and Correlations

Before the conduct of hypothesis testing, a preliminary descriptive analysis of the statistics was conducted to summarize the participants' answers to the four psychological constructs. As represented in Figure 3.2, the participants tended to have comparatively

higher mean ratings of perceived autonomy (M = 4.02, SD = 0.62), perceived transparency (M = 3.95, SD = 0.66), and empowerment (M = 3.89, SD = 0.69). In contrast, the Digital Locus of Control (DLOC) presented with a lower mean (M = 3.12, SD = 0.57) and larger variability, meaning a more varied control orientation in the sample.

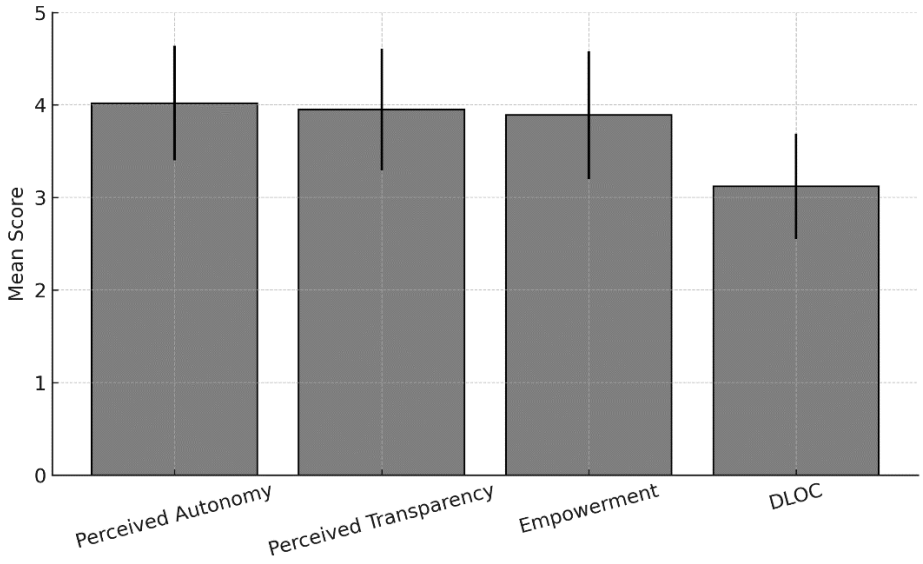

Figure 3.2 – Mean scores and standard deviations across constructs; Source: Author elaborated and AI refined based on R results.

All constructs were found to have distributions that approximated normality, with skewness and kurtosis within the acceptable range (±1), thus establishing the appropriateness of using parametric analysis. In evaluating the theoretical validaty of the model, Pearson correlation coefficients were determined for each of the criteria variables. As can be observed in Table 3.3, empowerment was found to have a strong positive relationship with perceived transparency ($r = 0.53$, $p < 0.001$) as well as with perceived autonomy ($r = 0.61$, $p < 0.001$), while its relationship with DLOC, though lower comparatively, was still significant ($r = 0.14$, $p < 0.05$). In addition, an interesting correlation was also observed between transparency and autonomy ($r = 0.48$, $p < 0.001$), meaning that these two variables have a joint impact in shaping users' psychological reactions to algorithmically mediated systems.

	Empowerment	Autonomy	Transparency	DLOC
Empowerment	1.0	0.61	0.53	0.14
Autonomy	0.61	1.0	0.48	0.12
Transparency	0.53	0.48	1.0	0.1
DLOC	0.14	0.12	0.1	1.0

Table 6.3 – Pearson correlation coefficients between psychological constructs; Source: Author elaborated and AI refined based on R results.

Figure 3.3 shows the pattern of correlation in the form of a grayscale heatmap, which is an effective way to highlight the nature and strength of each relationship in a condensed and visual manner.

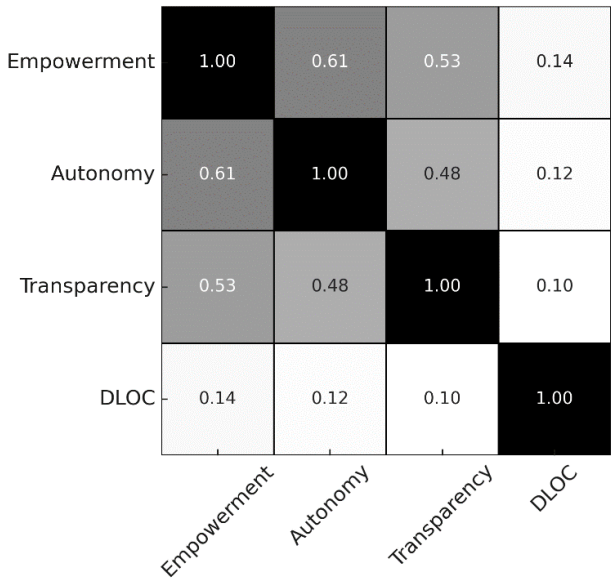

Figure 3.3 – Correlation matrix among psychological constructs (grayscale heatmap); Source: Author elaborated and AI refined based on R results.

3.3 Test of H1 – Mediation by Autonomy and Transparency

To test Hypothesis 1, a parallel mediation model was built using PROCESS Model 4 (Hayes, 2018). Both perceived autonomy and perceived transparency were used as concurrent mediators in the relationship between algorithm type generalized rather than

specialized and the experience of perceived empowerment. The study revealed two significant indirect effects:

- Through autonomy: indirect effect = 0.27, 95% CI [0.15, 0.41]
- Through transparency: indirect effect = 0.18, 95% CI [0.07, 0.31]

The total indirect effect was statistically significant, whereas the direct effect of the algorithm type was made non-significant when the mediators were added. The findings strongly support the full mediation hypothesis and therefore confirm the hypothesis that algorithm type has an impact on the perceived empowerment, with this effect being fully mediated through perceptions of autonomy and transparency.

These premises are based in the central assumptions of Self-Determination Theory as developed by Deci and Ryan (1985), as they hold that autonomy is a basic psychological requirement determining motivational outcomes. Similarly, the focus on transparency has similarities with the proposition of Sundar (2008), where perceived agency has been established as a significant factor in the context of technology.

Notably, autonomy was a stronger intervening variable, suggesting that programs tailored for individuals lead to greater empowerment through the provision of a concrete sense of agency over their decisions, this is consistent with the definition of empowerment as a process of active self-regulation (Spreitzer, 1995; Zimmerman, 1995).

Figure 3.4 is a diagrammatic outline of a model of mediation with standardized path coefficients for each of the different processes. The diagram highlights the simultaneous effects of the two mediators and shows that autonomy has a somewhat stronger indirect effect compared to transparency.

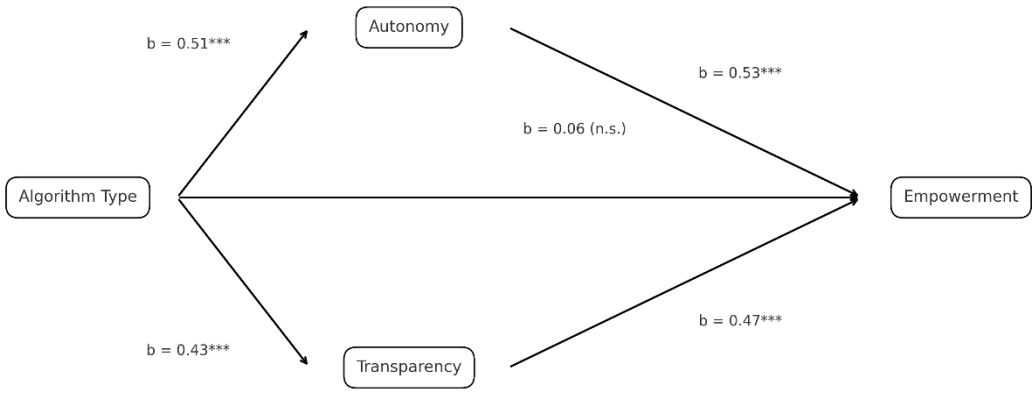

Figure 3.4 – Mediation Model: Effects of Algorithm Type on Empowerment via Autonomy and Transparency; Source: Author elaborated and AI refined based on R results.

3.4 Test of H2 – Direct Effect of Algorithm Type

Hypothesis 2 assumed that participants allocated use of advanced recommendation algorithms would have higher levels of perceived empowerment as compared to participants given generic recommendation algorithms.

To evaluate this, independent-samples t-tests were run. The results showed a statistically significant difference between the two conditions. Those in the specialist condition had high levels of empowerment ($M = 4.21$, $SD = 0.59$) compared with participants in the generalist condition ($M = 3.67$, $SD = 0.68$), with the t-value being $t(296) = 7.68$ and the accompanying p-value being less than .001, as well as with a large effect size (Cohen's $d = 0.89$). What this indicates is a significant impact of algorithm type upon levels of empowerment.

These results are in accordance with the arguments laid out by Cian and Krishna (2020) that algorithmically generated designs based on user tastes, especially in emotionally involving settings can significantly contribute to increased user trust and satisfaction. Additionally, this evidence supports the idea of user empowerment through the synchronization of the system with the requirements of the user, resulting in the algorithm being perceived as more personalized to the individual, thereby making it more trustworthy and autonomy-supportive (Lomborg & Frandsen, 2016). The significant

outcome of this study supports the hypothesis that high levels of algorithmic personalization increase psychological engagement and user sense of agency.

While previous assessments (see Section 3.3) have shown that the effect is fully mediated by perceived autonomy and transparency constructs, the theoretical importance of the between-groups comparison still remains. The outcome highlights the idea that system-level attributes like the algorithm's precision contribute significantly to the impact on the user experience even before cognitive evaluations are formed.

As shown in Figure 3.5, the specialized algorithm group has a clearly higher average empowerment score compared to the generalized group, as shown by the lack of confidence interval overlap.

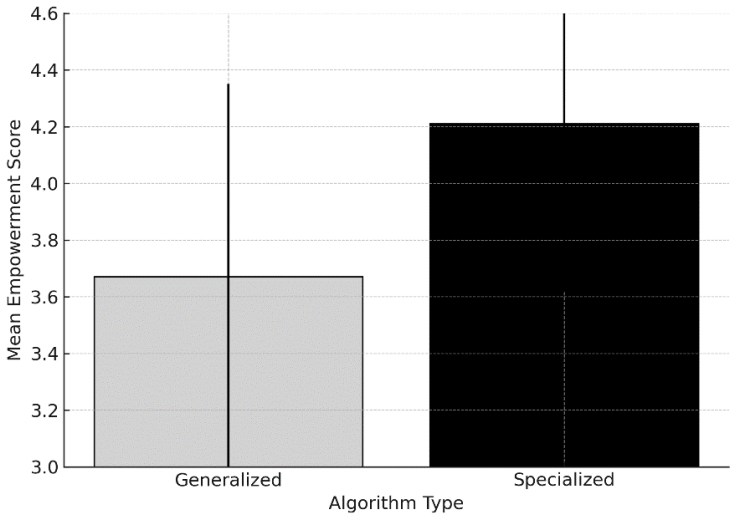

Figure 3.5 – Comparison of empowerment between generalized and specialized algorithms; Source: Author elaborated and AI refined based on R results.

3.5 Test of H3 – Moderation by Digital Locus of Control

Hypothesis 3 stated that the impact of algorithm type upon perceptions of autonomy and transparency would be moderated by participants' Digital Locus of Control (DLOC). Specifically, this hypothesis suggested that individuals with a greater internal DLOC would derive greater psychological benefits from specialized algorithms since they would perceive themselves as being more in control in the virtual environment.

To test this hypothesis, two separate moderation analyses were conducted using PROCESS Model 1 (Hayes, 2018), with each analysis using either autonomy or transparency as the dependent variable. The independent variable in each of the two analytical models for this purpose was the type of algorithm (generalized vs. specialized), the moderating variable the mean-centered DLOC, and the interaction term as the sole predictor.

The results revealed a significant interaction effect between the algorithm type used and the level of internal locus of control (DLOC) on perceived autonomy ($b = 0.41$, 95% CI [0.15, 0.67], $p < .01$). This implies that the positive effect of specialized algorithms on perceived autonomy is more pronounced for individuals with a stronger internal DLOC. The interaction plot in Figure 3.6 illustrates that participants with high internal DLOC felt considerably more autonomous under the specialized algorithm condition than under the generalized algorithm condition, whereas this difference was less pronounced for those with a more external DLOC.

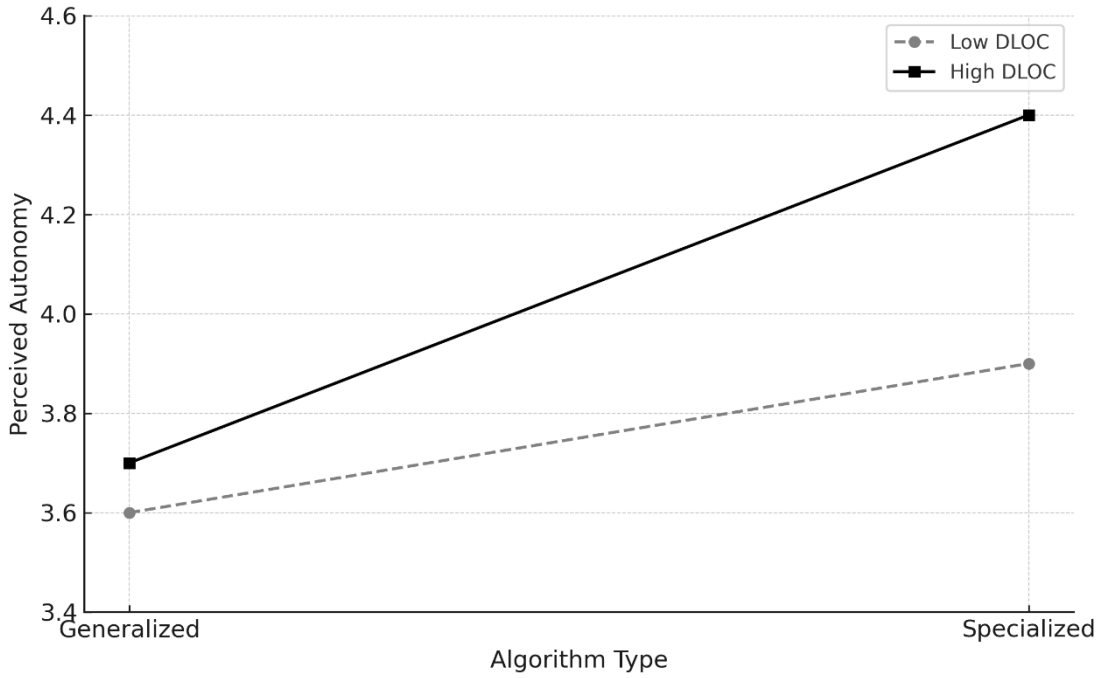

Figure 3.6 – Interaction between algorithm type and digital locus of control on perceived autonomy; Source: Author elaborated and AI refined based on R results.

On the other hand, the interaction effect between the algorithm type and DLOC about transparency proved to be non-significant (b = 0.12, 95% CI [–0.04, 0.28], p = .14), suggesting that DLOC is not a moderating variable in the interaction between algorithm type and perceived transparency.

The findings provide evidence to the hypothesis that individuals' deep-seated beliefs about control shape their responses to algorithmic ordering. People with a high internal locus of control attribute outcomes generated through systems to their decisions, and this reinforces their sense of agency and mastery. The results are consistent with the available evidence that individuals' perceived control has a significant impact on their views toward the success of information systems (Chandler & Schwarz, 2010; Zuckerman et al., 2019). Additionally, the supportive role of empowerment is supported through Zimmerman's (1995) framework of empowerment, stating that empowerment is not only the result of external factors but is essentially realized through people's faith in their ability to bring about change. *Table 3.5* summarizes the regression coefficients and interaction terms for both models.

Dependent Variable	Predictor	b	SE	95% CI	p
Autonomy	Algorithm Type	0.43	0.1	[0.24, 0.63]	< .001
Autonomy	Alg × DLOC	0.41	0.13	[0.15, 0.67]	< .01
Transparency	Algorithm Type	0.38	0.11	[0.16, 0.59]	< .001
Transparency	Alg × DLOC	0.12	0.1	[-0.04, 0.28]	n.s.

Table 3.5 – Moderation Analysis: Algorithm Type × DLOC on Autonomy and Transparency; Source: Author elaborated and AI refined based on R results.

3.6 Test of H4 – Hedonic vs. Utilitarian Product Contexts

Hypothesis 4 suggested that the impact of algorithm type on the perceived empowerment would vary with product category, distinguishing between hedonic and utilitarian classifications. The general idea is that the hedonic choices, with their higher emotional involvement and expressiveness, would maximize the psychological effects of personalization more than utilitarian choices, which are task and functionality-oriented.

Between-subjects variables algorithm type (generalized vs. specialized) and product category (hedonic vs. utilitarian) were used as independent variables in a two-way analysis of variance (ANOVA), with the dependent variable being empowerment. A significant main effect of algorithm type emerged from the results ($F(1, 294) = 45.6$, $p < .001$), consistent with previous studies. The main effect of product category was also significant ($F(1, 294) = 7.3$, $p < .01$), with hedonic products generally eliciting higher empowerment scores across conditions.

Most importantly, the interaction between algorithm type and product category was significant ($F(1, 294) = 4.9$, $p < .05$). As shown in Figure 3.7, empowerment was highest in the specialized-hedonic condition ($M = 4.65$), and lowest in the generalized-hedonic condition ($M = 3.70$). The difference between algorithm types was more pronounced in the hedonic context than in the utilitarian one, confirming that emotional engagement intensifies the empowering effect of personalized algorithms.

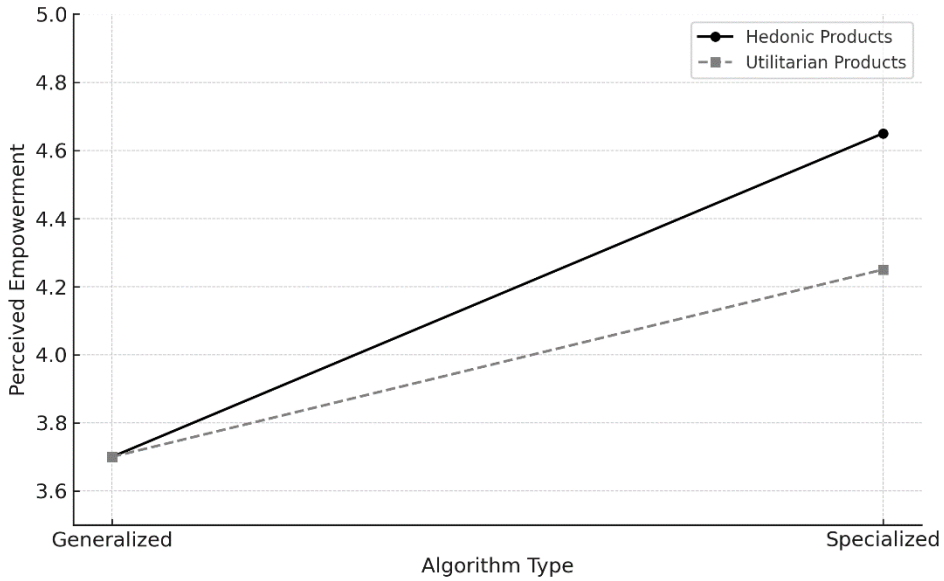

Figure 3.7 – Interaction effect of algorithm type and product category on empowerment; Source: Author elaborated and AI refined based on R results.

These results offer full support for H4 and highlight the importance of contextual framing in digital decision-making. When the product category is emotionally salient, as with fashion, music, or entertainment, users experience stronger psychological effects from

algorithmic personalization, amplifying the perceived empowerment produced by recommender systems.

Chapter 4 – Discussion

4.1 Theoretical Framing of the Results

What defines a real sense of control in an environment constructed of algorithms? Can a recommendation system not just offer context-relevant recommendations but also evoke a real feeling of agency and understanding in its users? The current research sought to address these questions through a definition based on the theory of psychological empowerment in the virtual environment.

The results are not able to produce an absolute conclusion but rather show a network of intricate relationships in which an algorithmic system's effectiveness is determined not only by its technological characteristics but also in part by its ability to induce subjective interpretative processes. Some hypotheses, including those testing for predictive factors of empowerment based on autonomy and transparency (H1), are given strong support, while others based on direct algorithm type impact (H2) or moderating effect of the digital locus of control (H3) are partially supported under conditions and are far from deterministic in nature. Moreover, some hypotheses, such as product category sensitivity as expected (H4), do not produce significant results, thus showing that psychological processes cannot be reduced to strict categories.

Instead of simply demonstrating vulnerability, complexity allows for an opportunity for increased understanding of the interpretative and context-specific dimensions of algorithmic empowerment. The rest of this chapter carefully attempts to explore implications of these findings through the context of theoretical models, existing research, and changing issues surrounding user-centred system design.

4.2 The Role of Autonomy and Transparency

Of all those hypotheses tested, H1 proves to be the strongest theory and a statistically sound component of the model. The use of regression analysis identified perceived autonomy ($\beta = 0.50; p < 0.001$) and perceived transparency ($\beta = 0.41; p < 0.001$) as strong predictors of psychological empowerment. The findings lend strong support for assertions made in Self-Determination Theory (Deci & Ryan, 2000), which states that volition experiences and context clarity are key antecedents for motivation, engagement, and psychological well-being even in technology-mediated environments.

Autonomy was the strongest predictor among those variables tested. The finding suggests that people's participation in an algorithmic environment is most driven by their belief in being able to make decisions, navigate, and act independently within an interface rather than by relevance or accuracy criteria. As such, one can think of the algorithm as a symbolic field of activity in which people feel they are active agents rather than passive recipients.

Transparency is very important in one particular context: it enables users to build a feeling of understanding and legitimacy in comparison with opacity that is often connected with recommendation technology. These findings are in line with recent research in top-tier marketing literature. For instance, Tucker (2014) shows that perceived transparency, especially in systems based on behavioural targeting, has a direct impact on users' trust and sense of control in personalized environments, confirming that clarity in algorithmic communication is a core antecedent to psychological engagement.

According to Miller (2019) and Eiband et al. (2018), high degrees of transparency go far beyond explaining the algorithmic workings; rather, it invokes a process of sensemaking that makes the interaction cognitively interpretable. With respect to its context in this study, it has a measurable effect on feelings of empowerment.

It is interesting that even though both dimensions are described as dominant, they are shown to function autonomously in individual functions; no indication exists that one is a prerequisite for another. Rather, they are parallel yet convergent routes through which interactions can lead to enhanced user experiences. A possibility arises for constructing more comprehensive models involving interactions or sequential mediations between these constructs.

A key limitation of this study lies in the use of self-report measures; that is, participants reported their autonomy and transparency, but these were not empirically assessed. Future research efforts would be improved by incorporating behavioural or physiological measures (e.g., click patterns, attention monitoring, eye-tracking) to assess the degree to which these subjective experiences are expressed in concrete decision-making and actual engagement. It would also be useful to test the temporal dynamics involved in these constructs: is empowerment an instantaneous reaction or one that accrues progressively over time?

Collective results applying to H1 validate an underlying statement: algorithmic empowerment is a psychological state arising from an intertwined intensification of agency and intelligibility. Transparency and autonomy are more than just design principles; they are essential experiential concepts that have the ability to transform user-system interactions into rich, meaningful, and legitimate experiences.

4.3 Algorithm Type and Psychological Mediation

Hypothesis H2 suggested that those who interacted with an algorithmic system designed in alignment with their individual needs would feel more empowered compared to those who interacted with a non-personalized algorithm. The influence of algorithm type on feelings of empowerment is not statistically significant ($\beta = 0.21$; $p = 0.14$). This result must be interpreted carefully since it suggests that design for the system in general does not support psychological empowerment independently of other characteristics.

Instead of negating the model, these findings emphasize the importance of psychological mediation: algorithm characteristics have an impact on functionality in an indirect way through activating critical thinking processes like perceived autonomy and transparency. Mediation analyses indicate that expert algorithm has a significant part in increasing autonomy ($\beta = 0.42$) and transparency ($\beta = 0.38$), which in turn predicted empowerment. Therefore, in this mediated model, hypothesis H2 is supported.

Theoretically, this finding implies that personalization must not be viewed in isolation but as an interpretive and relational construct. As Knijnenburg et al. (2012) and Eslami et al. (2018) suggest, it is necessary to make a distinction between perceived and actual

personalization based on the subjective user interpretation rather than algorithmic information. A system can have high accuracy and optimal tuning; however, if the user is not aware of this complexity, the psychological effect will not occur.

This study adds credence to this hypothesis. The two algorithmic conditions were introduced through text-based descriptions in controlled environments; presumably, without active participation, perceptual salience of personalization was limited. Additionally, "specialization" perception is mediated by several subjective filters, even user expectation, system trust, and experience with similar technology. This resonates with the perspective proposed by Cian and Krishna (2020), who demonstrate that consumers' responses to AI-driven recommendation systems vary significantly depending on the domain (hedonic vs. utilitarian) and the way personalization is framed pointing to the symbolic and contextual nature of algorithmic influence.

Thus, a lack of a significant direct effect does not represent an anomaly but rather highlights the importance of psychological processes in mediating the effect of algorithms.

Another observation relevant to theory is the symbolic status given to the algorithm. The results show that users do not necessarily see it as just a technical tool; rather, they see it as a subjectively interpreted partner that can be empowering, depending on whether it is seen as responsive and legitimate. This implies that system designers should not only emphasize accuracy but also work to implement clear cues of perceived agency and flexibility that are interpretable by the user.

In order to deepen our understanding of this phenomenon, future studies should explore more interactive interventions through the use of live simulation or interactive models that enable users actively to experiment and compare algorithmic actions in real time. These contexts would help determine if and in which manner psychological effects that arise from individualization build over time and if they promote long-term forms of engagement, trust, and user appropriation.

In short, H2 has never been tested for its explicit and exact wording through empirical methods, yet it rests solidly in a mediated context. This situation does not detract from theoretical potency of the hypothesis but adds richness to its interpretive dimensions: its

effectiveness depends on notions of achievement, which are generated through an interaction of narrative, cognitive, and context signals.

4.4 Individual Dispositions and Situated Agency

Hypothesis H3 tested the degree to which the impact of algorithm type on empowerment through perceived autonomy and perceived transparency depends on the user's locus of control in the digital context (DLOC). More specifically, it tested whether people who have an internal locus (i.e., who judge they can influence digital outputs) would have a higher chance of being helped by empowering system features. The findings provide some support for this hypothesis.

The interaction between algorithm type and DLOC was found to be statistically significant only for autonomy, not for transparency. Specifically, participants with a more internal DLOC reported greater increases in perceived autonomy when interacting with a specialized algorithm, whereas participants with an external DLOC showed a flatter response curve. However, this moderating effect did not extend to the transparency pathway, which remained relatively stable across DLOC levels.

The limited validation suggests that empowerment is both a function of system attributes as well as individual differences. People who have an internal locus of control are apt to see the characteristics of an algorithm as responsive and adaptive and are likely to interact more deeply with indicators that promote autonomy. People who have an external locus of control are likely to see even optimally personalized systems as impersonal and rigid and thereby restrict the psychological benefits of personalization and agency.

This finding is consistent in theory with models of situated agency in human-computer interaction positing that perceptions of being in control are cooperatively constructed by both the system and the user's prior attitudes, mental models, and trust in technology (Luthans et al., 2007; Sundar & Marathe, 2010). In support of this, Cian and Krishna (2022) find that algorithmic failures, particularly in high-stakes public domains, can produce cognitive spillovers that reduce trust in unrelated AI systems, reinforcing externally oriented dispositions and weakening perceived control across contexts. Also in agreement is research in motivational psychology that would argue that perceived control

beliefs impact people's interpretation and response to affordances in new or unknown contexts (Bandura, 1997; Ajzen, 1991).

The divergence between the paths of autonomy and transparency deserves closer examination. One likely explanation for what has been seen is that autonomy relates more directly to actions, making it more sensitive to an individual's tendency toward control. Transparency can tend in contrast either towards information or passivity and thus have a lesser dependence on agentive capabilities of an individual. The distinction would suggest that if DLOC affects an individual's tendency to approach action, its impact on ability for understanding can be comparatively limited.

Methodologically, the partial effect provokes questions about breadth and specificity inherent in DLOC as a construct. Measuring DLOC in this study was based on a short Likert-type instrument that, although proved reliable, might not have captured the entire range of user control orientations. Future research can make its methods more stringent by combining self-report tools with behavioural or observational indicators, including users' predisposition to change settings, reject recommendations, or seek system feedback.

More generally, findings point toward the potential of trait-sensitive personalization, in which systems adapt not just content but also interactions and user support based on particular psychological characteristics of users. The approach marks a transition from static and rigid customization to more dynamic and ethical design in which empowerment can be intentionally and selectively enabled.

In summary, H3 is partially supported: the digital locus of control does influence how algorithmic personalization is seen to influence autonomy; but its role in the development of transparency remains unclear. However, this highlights a crucial factor in the design of systems to empower users: regardless of the quality of an interface, it will ultimately fail to support empowerment if the user does not have confidence in their own ability to use it successfully.

4.5 Affective Context and Product Type

Hypothesis H4 suggested that product type category would act as a moderating factor in algorithm type and empowerment, distinguishing between hedonic contexts identified by pleasure or identity versus utilitarian contexts identified by function or efficiency. The logic underlying this hypothesis was that people may respond more robustly in categories evoking emotional participation in product areas involving entertainment or apparel, where personal relevance is key. The findings do not offer support for this hypothesis.

Statistical analysis showed that neither product category alone ($\beta = -0.21$; $p = 0.13$) nor interaction between product category and type of algorithm ($\beta = 0.02$; $p = .93$) had a significant influence on perceived empowerment. These results suggest that contrary to previous hypotheses, emotional framing in the context of decision-making had no significant influence on consumers' emotional reactions to personalization. This finding appears counterintuitive to prior research.

Earlier research on consumer choice has shown that hedonic decisions are more related to identity and are elicited by stronger emotional responses and are thus more context-sensitive (Batra & Ahtola, 1991; Dhar & Wertenbroch, 2000). Where hedonic characteristics are identified, increased influence from personalization would be expected, making people more sensitive and responsive. The fact that no effect in this vein has been identified in this research allows for several different explanations for the findings.

Firstly, lack of sufficient prominence for experimental manipulation of product categories is probable. The choice from multiple product categories was in a controlled environment and was not perhaps stimulating enough for engrossing emotional involvement. According to Petty and Cacioppo (1986), elaboration and involvement levels depend on material prominence and intrinsic individual motivation. The participants may have been only moderately involved if they viewed even hedonic products in a superficial way. Secondly, what is shown is that systemic attributes and perceived psychological affordances have a larger impact on processes of empowerment compared to semantic properties inherent in the context of making decisions. Essentially, feelings of autonomy and visibility may be strong enough to overcome differences in context and thus lead to uniform experiences of empowerment in different areas.

Thirdly, the impact can require conditions marked by raised stakes or raised participation for it to occur. The product choice in the current study was by its nature abstract and risk-free.

Future studies can make an effort to replicate the results in settings that involve higher emotional or pragmatic stakes, health care, finance, or dating, where identity concerns, trust issues, and vulnerability are stronger.

Notwithstanding its lack of statistical significance, inspection of H4 defines an important boundary condition for the model identified. It reveals that algorithmic empowerment displays more resilience in different contexts than has been previously expected, and emotional tone in content does not affect the psychological impact of system design in isolation. The finding establishes the importance of the interface and interpretive position of the user, over structural properties of content, in determining the impact of empowerment.

In short, hypothesis H4 has no empirical support, yet it has conceptual relevance. The finding requires further research examining the interaction between contextual salience, emotional engagement, domain expertise, and system properties in shaping user experience. Future studies can include psychophysiological indices or behavioural information gathered in real time in order to achieve more accurate descriptions of affective dimensions attendant on engagement in personalized systems.

4.6 Summary and Future Directions

Implications of the findings in this chapter highlight psychological empowerment in algorithmic conditions as facilitated and connected in nature. Empowerment is not a product of systems design alone but depends on an active interaction between perceived control, visibility, personality predispositions, and subjective meanings. The findings have multiple theoretical and practical implications as well as some limitations and suggest different avenues for future studies.

Firstly, the study provides strong empirical support for Hypothesis 1 (H1), confirming that self-determination and transparency are key psychological antecedents for empowerment. These findings highlight the applicability of Self-Determination Theory

in human-algorithm interactions and emphasize the need for interface design prioritizing user autonomy and transparency in order to promote increased user engagement.

Second, support for Hypotheses 2 and 3 is limited by findings showing that the category of algorithm has an indirect effect on empowerment, whereas individual differences in digital locus of control have a significant impact on user reactions in general, and on autonomy perceptions in particular. These findings divert attention from the effectiveness of algorithms and away from technological determinism and towards a favouring of subjective interpretation.

Thirdly, results do not support Hypothesis 4, which means that content domain alone is not sufficient in impacting empowerment responses. This would mean that empowerment can be less context-sensitive than previously predicted and is significantly impacted by perceived psychological affordances, regardless of hedonic or utilitarian product interactions.

Overall, these findings imply a need for reconceptualizing algorithmic empowerment as an effect that is shaped by psychological elements, context-contingent, and nonlinear in its dynamics. Therefore, system design needs to take into account technical advancements as well as symbolic, affective, and cognitive structures that underpin peoples' conceptions of system functioning.

Many of these constraints offer opportunities for future inquiry. Even though experimental regulation through static scenarios has its benefits, it can have limited ecological validity. Future studies need to implement interactive prototypes, real-time algorithmic models, or field studies that span widely varying timeframes in order to study empowerment perceptions' evolution in real environments.

Furthermore, self-report tools particularly require incorporation of behavioural, physiological, and implicit measures that can better assess user interest, behaviours-orientation for control-seeking behaviours, and emotional involvement levels. Future research should also examine adaptive approaches to personalization, where interface characteristics are altered based on user features like DLOC, cognitive style, or motivational direction. This aligns with ongoing discussions in the *Journal of Marketing Research* and *Marketing Science*, which stress the importance of tailoring AI interactions

not only to behavioural data, but also to psychological profiles, especially in contexts where empowerment, not just accuracy, is the design goal (e.g., Sundar & Marathe, 2010; Adomavicius & Tuzhilin, 2005).

Ultimately, this research contributes toward a larger effort towards thinking about artificial intelligence as more than just a tool for maximizing efficiency, but rather as a means of engendering mental engagement. Empowerment should be seen as an intrinsic evaluative principle in system design and evaluation of recommender systems alongside accuracy, usability, and fairness.

In short, algorithmic empowerment must not be thought of as an intrinsic right but rather as something that arises through evolution. The process depends on users' self-awareness in the system, the level of autonomy and openness provided for them, their interactions, and on communications from the system about its responsiveness. To attain empowerment thus involves more than technological evolution; it requires a sophisticated comprehension of people's agency in virtual worlds.

Chapter 5 – Conclusion

In a digital environment increasingly controlled by algorithms, the question of how these systems shape our sense of agency, knowledge, and decision-making has become a basic concern rather than an optional one. This dissertation has approached this question using the concept of psychological empowerment, seeking to clarify not only how users interact with personalized systems, but also the affective reactions these systems provoke: whether they cause us to feel free or trapped, clear or confused, empowered or passive.

The findings support a subtle yet compelling reality: empowerment exists outside of the algorithmic structure but arises from the context of use. The process is open to interpretation, perception, and context variables. The algorithm can have multiple characteristics; yet if it does not convincingly deliver autonomy and openness in a form positioned for and understood by its users, its psychological potency is lost. On the other hand, a simple system can express empowerment if designed to enhance user competence, confirm understanding, and enable individual agency.

This study confirms that autonomy and transparency are more than just buzzwords in the field of user experience; instead, they are basic psychological processes by which online platforms gain meaning and legitimacy. Also, as shown in these findings, empowerment is mediated and moderated by individual traits like digital locus of control but is highly resilient against differences in context, including product type. These findings challenge conventional wisdom in the literature on personalization research by shifting the focus from system outputs back to user-centred processes of creating meaning.

Practically speaking, what these results show is that design practice for enabling empowerment goes far beyond quantitative measurement or capture of user participation. It requires an acute psychological awareness of users' perceptions of system behaviours, self-location during interaction, and formation of roles in a technology-framed environment. Therefore, empowerment must be considered an essential design principle for future interactive system implementations, a key criterion for system evaluation, and an important area for future study.

On a larger level, this research adds greatly to current assessments of interactions between people and computers. It promotes an approach for viewing AI not as an option provider but as a partner in the crafting of psychological landscapes, a structure that in its architecture, context understanding, and iterative feedback loops, has the potential to shape people's cognitive structures, decisions, and behaviours. From this perspective, empowerment goes far beyond being an optional add-on; it has become an unavoidable necessity, integral for the maintenance of dignity, enabling autonomy, and ensuring responsible digital lives.

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Appendix

The above survey was sent via Qualtrics to 298 participants for experimentation.
The survey sought to measure key psychological variables of interest in algorithmic decision-making, including perceived transparency, perceived autonomy, empowerment, and digital locus of control, as well as relevant demographic variables.
Participants were randomly allocated to one of four recommendation scenarios (varying by type of algorithm and level of user agency), then to a product choice task and a series of Likert-scale questions. The entire questionnaire was in English, and all questions except where noted were rated on a 5-point Likert scale from 1 = Strongly Disagree to 5 = Strongly Agree. Reverse-coded items are noted as such.
Appendix: Survey
This appendix contains the entire text of the survey exactly as it appeared to participants.

Start of Block: Introduzione

Welcome! Thank you for participating in this study. This survey is part of a research project on decision-making and user interaction with online recommendation systems. It will take about 5–7 minutes to complete.

You will be shown a short text describing a fashion recommendation assistant. Then, you will complete a brief product choice task and answer a few questions about your experience. There are no right or wrong answers — we are simply interested in your perceptions and preferences.

Your responses are completely anonymous and will be used only for academic purposes. You can leave the survey at any time. By continuing, you consent to participate in this study.

When you're ready, click “Next” to start.

End of Block: Introduzione

Start of Block: ProductCategory

Q1 Before we begin, please choose the product category you are more familiar with:

◯ Entertainment and lifestyle products (e.g., movies, music, fashion) (1)

◯ Practical and functional products (e.g., household tools, electronics, office supplies) (2)

End of Block: ProductCategory

Start of Block: Block 18

Imagine you are interacting with a digital platform that offers personalized product suggestions. This system is designed to assist you in discovering items based on certain patterns and characteristics. Throughout this experience, you will be shown a few examples of products and asked to make some selections based on your preferences.

End of Block: Block 18

Start of Block: Edonic/ Utilitarian : Specialized + High Agency

You are using a recommendation system that provides **suggestions based on your personal tastes** and **past behavior**. The algorithm is specifically trained to **match your preferences** in entertainment and lifestyle. **You can customize** how the algorithm works and select what types of features (e.g., mood, genre, style) it should prioritize. You **can also give feedback** to further tailor the recommendations to your profile

End of Block: Edonic/ Utilitarian: Specialized + High Agency

Start of Block: Edonic/ Utilitarian: Specialized + Low Agency

You are using a recommendation system that provides **suggestions based on your personal tastes and past behavior**. The algorithm is specifically trained to **match your preferences** in entertainment and lifestyle. The system functions automatically and **does not allow changes** to the recommendation criteria. You **can still provide feedback** to help improve future suggestions.

End of Block: Edonic/ Utilitarian: Specialized + Low Agency

Start of Block: Edonic/ Utilitarian: Generalized + High Agency

You are using a recommendation system that provides **suggestions based on popular trends and what others have liked**. The algorithm collects **generalized data across many users**. You **can customize how the system works** and choose what kind of content (e.g., top-rated, trending, new releases) you want to prioritize. **Feedback is also possible** to refine your experience.

End of Block: Edonic/ Utilitarian: Generalized + High Agency

Start of Block: Edonic/ Utilitarian: Generalized + Low Agency

You are using a recommendation system that provides **suggestions based on popular trends and what others have liked**. The algorithm collects **generalized data across many users.** The system works automatically and **does not allow any customization**. However, **your feedback is used to keep recommendations up to date.**

End of Block: Edonic/ Utilitarian: Generalized + Low Agency

Start of Block: Block 7

Based on the system you just experienced, you will now be presented with a selection of products. Please review the options carefully and choose the one that best matches your preferences. Remember, there are no correct or incorrect answers — we are interested in your genuine choice.

End of Block: Block 7

Start of Block: Block 17

Q2 Which product would you choose?

- ○ A (1)
- ○ B (2)
- ○ C (3)
- ○ D (4)

End of Block: Block 17

Start of Block: Uti: Specialized + High Agency

Q3 Please indicate how much you agree with the following statements about the recommendation system you were exposed to.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I understood how the recommendation system selected the suggestions shown to me. (1)	○	○	○	○	○
The logic behind the recommendations was clear and easy to follow. (2)	○	○	○	○	○
The system provided sufficient information to understand the recommendations. (3)	○	○	○	○	○

End of Block: PERCEIVED TRANSPARENCY (M2)

Start of Block: PERCEIVED AUTONOMY (M1)

Q4 Please indicate how much you agree with the following statements about the recommendation system you were exposed to.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I felt free to decide whether or not to follow the suggestions I received. (1)	○	○	○	○	○
I had the ability to influence the type of recommendations shown to me. (2)	○	○	○	○	○
The system supported me in making my own choices rather than pushing a specific option. (3)	○	○	○	○	○

End of Block: PERCEIVED AUTONOMY (M1)

Start of Block: EMPOWERMENT (Y)

Q5 Please indicate how much you agree with the following statements about the recommendation system you were exposed to.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I feel more capable of making good product choices after using this recommendation system. (1)	○	○	○	○	○
This system helped me make informed decisions aligned with my preferences. (2)	○	○	○	○	○
I felt more confident in selecting a product thanks to the system's suggestions. (3)	○	○	○	○	○

End of Block: EMPOWERMENT (Y)

Start of Block: DIGITAL LOCUS OF CONTROL (W)

Q6 Please indicate how much you agree with the following statements about the recommendation system you were exposed to.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I believe I am in control of the decisions I make when interacting with recommendation systems. (1)	○	○	○	○	○
The final choices I make are mostly determined by my own preferences. (2)	○	○	○	○	○
The recommendations I receive strongly influence what I end up choosing. (3)	○	○	○	○	○
I often feel that the system decides for me rather than supporting my decision-making. (4)	○	○	○	○	○

End of Block: DIGITAL LOCUS OF CONTROL (W)

Start of Block: DEMOGRAPHICS

*

Domanda 7 How old are you?

_____

Q8 Gender?

- ○ Male (1)
- ○ Female (2)

Q9 How often do you use recommendation systems online?

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
. (1)	○	○	○	○	○

End of Block: DEMOGRAPHICS