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Review

Recognising the Importance of Preference Change: A Call for a Coordinated Multidisciplinary Research Effort in the Age of AI

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ABSTRACT

Knowing and controlling how AI systems affect our lives and choices is crucial as AI becomes stronger and more pervasive in everyday life. As an example, personalized recommender systems learn users' preferences to provide suggestions that alter online behavior; this is only one example of how modern ML systems often influence user behavior. Changes in preference are an externality of behavior modification. To better understand how AI systems alter preferences, this paper argues for the creation of a multidisciplinary effort called Preference Science. We provide a conceptual framework for the evolution of preferences, explain the significance of meta-preferences and preference-change preferences, and operationalize preference in terms of integrated ideas from other fields. We differentiate between changing one's preferences, changing one's preferences in a way that is authorized, and manipulating preferences in an explicit manner. This paradigm benefits from the unique insights provided by a variety of disciplines.

Keywords
Artificial intelligence (AI); Machine learning (ML).

INTRODUCTION

In order to tailor a service to each user's tastes, modern AI often employs Machine Learning techniques that may learn their preferences (e.g., favorite musician) (Domshlak et al. 2011). According to Ibrahima and Younisb (2018) and Yakhchi (2021), user preference on online platforms is usually deduced from consumer behavior, such as what the user has listened to, or consumer ratings, such as whether the user clicked the "like" or "dislike" button. According to Jesse and Jannach (2021), consumers' online activity is influenced by the personalized suggestions. In order to affect people's actions, behavior change practitioners employ behavioral insights, which are a cause-and-effect knowledge of how circumstances shape behavior at the population level, to alter people's decision architecture (Ruggeri 2018). According to Michie, Van Stralen, and West (2011), research in behavioral science has provided a solid foundation for understanding behavior and its dynamics, which in turn has allowed for the creation of precise prediction models.

User interactions with AI-powered systems that have been designed with Behavioral Science in mind are clearly behavior change as a result of ence. The fact that these behaviors also lead to a shift in preference is less obvious. While preferences certainly have an impact on how we act, the reality is that most of the time, our actions come first and then give rise to new preferences (Ariely and Norton 2008). Because behavior modification specialists morally justify their work by claiming they just impact behavior and do not restrict or force choices, this is a problem (Sunstein 2016). One rationale for using AI to personalize experiences for users is the desire to better understand platform users and cater to their needs. The current shift in taste leads us to believe that behavioural science and artificial intelligence may be much more manipulative in their practises (Sunstein 2015). Therefore, knowing how these technologies affect preference is crucial for ensuring the ethical and safe usage of AI. Without recognizing that AI has the ability to alter human preferences, any effort to direct AI so that its "ob-jective is to maximise the realization of human preferences" (Russell 2019) would be fruitless.

In order to achieve this goal, this essay presents the case for a multidisciplinary effort to quantify preferences in a wider sense and study their dynamics. For simplicity's sake, we'll call this effort "Preference Science" throughout this piece. Its stated goal is to address fundamental concerns in launching this project. To begin with, it aspires to operationalize preference in a manner that draws on aspects of the notion from many fields to increase our comprehension of it. Secondly, it takes into account preference-change prefer-ence, which is a person's preference about the process by which their preferences are created, and meta preference, which is a person's choice regarding their own preferences, both now and in the future. Thirdly, it suggests a structure for comprehending the evolution of preferences. The paper will conclude by suggesting a scientific avenue for further study into the dynamics of preference evolution.

SPreference redux

Disciplines unique to the social sciences have developed methods for studying and operationalizing preference and related concepts1. Preferences' salient features are illuminated by each of these fields. A choice's definition should take this into consideration, in order to provide a stronger operationalization of preference. We suggest that preference be characterized as any mental process that results in a liking or disliking for anything, whether it is explicit, conscious, and reflective or implicit, unconscious, and auto-matic. By include additional ideas related to conative psychological processes, this definition expands the range of preference. Rather of describing their surroundings, conative mental states work to create them. Mental states that are conative teach us about how the world should be, and mental states that are cognitive teach us about how the world really is (Schulz 2015).

Affirmative and negative statements

Opting amongst several alternatives is a common way that preference is defined in economics. Picking one option over another shows that you have a preference for that one. According to Samuelson (1938), this is an instance of a "revealed preference," where the agent's behavior is taken for granted as evidence of the choice. Since people lack the resources of perfect rational machines, it is evident that this is just a partial description of choice. Recognizing that people are "bound- edly rational" (Simon, 1955), or mostly rational with some defects, has led to the development of approaches to exploring preferences that take this into account. You can't figure out an agent's ratio-nality and preferences just by watching them, as Armstrong and Mindermann (2018) prove in a formal way.

The term "stated preferences" (Kroes and Sheldon 1988) is often used in philosophy and some branches of social science to describe the process of explicitly inquiring about an agent's preferences. Issues arise from the fact that individuals may not be truthful in their choices (Sunstein 2018b) and might be swayed by the wording of the questions (Thaler and Benartzi 2004; Sˇpecia'n 2019).

Both decision-making and object-judgment, namely like-or-dislike, are used to operationalize preferences in psychological research (Kahneman and Tversky 1982). A person's past actions, social circle, and physical surroundings may all have an impact on their preferences, according to researchers in the subject (Michie, Van Stralen, and West 2011; Cialdini 1987).

For psychologists, there is a difference between a want and a preference (Pettit 1998; Schulz 2015). In contrast to preferences, which center on weighing available options, desires are object-specific. Therefore, a preference may be defined as a comparison of wants. The strength of one's desires is proportional to the object's perceived value. When people make relative evaluations between alternatives rather than absolute assessments towards a given thing, they demonstrate various judgments for the same object (Azar 2011; Bazerman, Loewenstein, and White 1992). For this reason, preference science is concerned with both conative states.

Machine learning preferences

These days, businesses rely on individualized recommender systems built with data gleaned from extensive user preference research conducted by machine learning experts. One goal of personalized recommender engines is to mimic user preferences so that they can provide consumers a more relevant set of recommendations on a given platform. They do this by analyzing the user's past actions.

Here we have an example of revealed preference in action. The ineffectiveness of systems that use user ratings of platform content as a proxy for their stated preferences has led to their widespread deprecation. Successful recommender systems employ collaborative filtering, which presupposes that users' tastes are comparable to those of other users who exhibit comparable behavior or have comparable backgrounds.

When developing commercial recommender engines, it is important to keep the platform's interests in mind. As a result, these engines target user behavior in an effort to increase clicks, purchases, and platform engagement. Because of the two-way causal relationship between a user's preferences and their actions on the website, recommender engines may influence their preferences over time by encouraging them to consume certain types of content (Evans and Kasirzadeh 2021). According to Alfano et al. (2020), in order to keep users engaged, this kind of algorithm would suggest extremist material. This might lead to the formation of online echo chambers and polarization on social media platforms. More in-depth discussion of the general topic of AI systems influencing user preferences may be found in Ashton and Franklin's future work.

Choices in the field of behavioral science

To better explain preferences, prominent behavior change frameworks in behavioral science have uncovered conative mental states. Additionally, the frameworks detail what is needed to set up a preference change framework. According to the COM-B model, which was put out by Michie, Van Stralen, and West (2011), there are three main factors that contribute to every behavior: capability, opportunity, and motivation. More than any other activity, in order for a person to act, they must believe they can, have the chance to, and want or need to carry out the action. Changes in behavior are the outcome of the interplay between the three components. The Behavior Change Wheel is an add-on to this model that explains how Choice Architecture, the pervasive and powerful contexts in which individuals act, affects the COM-B components (Michie et al. 2014).

The term "capability" may refer to an individual's mental or physical abilities. The term "opportunity" may refer to opportunities presented by either the social (containing things like cultural norms, expectations, and social signals) or the physical (including things like time, resources, and location) environment. An individual's conative psych- chological processes that are involved in behavior, and are thus applicable to our broader definition of preference. It is a mental state which relates to people's initiation, contin- uation, and termination of certain behaviors at a particular time. Motivation, in other words, brings about an explicit or implicit liking or disliking for behaviors. COM-B uses a dual-process approach to recognize that motivation can oc- cur due to both automatic and reflective processes. Reflec- tive motivation includes conscious mental processes includ- ing attitudes and beliefs, while automatic motivation is an umbrella term for less conscious mental processes including desires, emotional reactions, and habits.

The Theoretical Domains Framework (TDF) – a list of factors that influence behavior – identifies corresponding conative states that map onto the components of COM- B's reflexive and automatic motivation (Atkins et al. 2017). Here reinforcement (i.e., an automatic response to a stimu- lus) and emotion map onto automatic motivation. Social/pro- fessional role and identity, beliefs about capabilities and consequences, intentions and goals map onto reflexive mo- tivation.

Three things become evident from the behavioral science literature. First, concepts that have not been traditionally thought of as preferences can be as they are conative states that bring about a sense of liking or disliking for something. Second, these conative states are not only conscious but also often automatic. Finally, preferences are shaped by multiple factors, thus, an individual's preferences will often change. Preference science must account for these factors, as well as for people's preferences towards their own preferences and how they change.

Meta-preference

People's preferences can conflict with each other – self- regulation can be seen as successfully privileging long- term goals over short-term pleasure (Doerr and Baumeister 2010). People will have preferences over which of these should win out, and at what cost; these preferences over preferences can be termed meta or second-order preferences. Humans can endorse or un-endorse some of their own preferences (Frankfurt 1988): for instance, people can har- bor sexist or racist instincts which they desire not to have.

And they can want to be a specific sort of person - even at a cost to themselves (Hewitt and Flett 1990).

Examples of preference conflict and resolution can happen when a subject is confronted with a novel situation or thought experiment beyond their normal experience (consider the trolley problem (Thomson 1976) or the repugnant conclusion (Parfit 1984)). People often resolve these conflicts in a contingent and non-consistent way, depending on the details of the circumstances they're in, their social environment, and how the issue is pre- sented (Payne et al. 1993; Schuman, Presser, and Ludwig 1981; Kleiman-Weiner, Saxe, and Tenenbaum 2017). But they also seem to have a desire for consis-

Many fields define some form of idealized preferences (Arneson 1989; Sunstein and Thaler 2003; Rosati 2009), and claim that truly serving a person's interest is to respect these idealized preferences. These idealized preferences are typically those that the person would have with, for instance, rational reflection, full information, no pressure, and enough time to ponder.

But those requirements are themselves meta-preferences, that determine the idealized preferences. It is very possible, for instance, for humans to feel that their true preferences emerge in the more emotional and dynamic parts of their lives (Bazerman, Tenbrunsel, and Wade-Benzoni 1998; Caplan 2001). Indeed, emotional decision-making can be more consistent than non-emotional (Lee, Amir, and Ariely 2009). Thus the very definition of idealized preferences – the definition of what it is to act in someone's best interests – depends on taking their meta-preferences into account3.

We believe meta-preferences are a necessary component for building any framework concerning the ethics of prefer- ence change.

Preference-Change Preferences

As well as meta-preferences, we must also recognise prefer- ences concerning the method of the formation process of any preference. Even if preferences meet the meta-preference re- quirements, how they get there is important; the ends do not always justify the means. This is recognised in the Article 5 of the draft EU AI Act (CNECT 2021), which prohibits the use of any AI system that deploys subliminal techniques...in order to materially distort a person's behavior in a manner that causes...that person or another person physical or psy- chological harm. Colburn (2011) argues that subliminal or unconscious preference change devices are wrong because they interfere with a user's autonomy. They are preferences which the user cannot correctly understand why they have, because they were unaware of the process which caused them. With this account preference manipulation and in- duced addiction are not acceptable practices whilst self in- duced processes like learning and character planning are.

Guidance concerning what behavioral change mech- anisms are and are not acceptable can be considered preference-change preferences given the causal relationship between behavior and preference. One guidance advocates for "a right not to be manipulated" (Sunstein 2021). Be- havior change is said to be manipulative if it does not en- gage with people's capacity for reflective choice (Sunstein 2015). Other guidance argues for "Nudge, not sludge" – making welfare-promoting behaviors easier to do, and re- moving sludge – behavior change strategies that have the be- havior change practitioner's best interest in mind rather than that of the target individual (Thaler 2018). Sludge is said to take two forms: discouraging a person's best interest or en- couraging self-defeating behaviors.

Guidance proposes for sludge audits – identifying the mech- anisms that change behavior and preference, and eliminat- ing those not in line with our preference-change preferences (Sunstein 2020). A final guidance comes from Libertarian Paternalism. Proponents of it argue that behavior change is ethical when it avoids material incentives and coercion, and it is used to give people a guidance for best practice given their own goals, rather than changing their end goals (Thaler and Sunstein 2003). Altogether, there is a strong rea- son to have a preference-change preference for preference change mechanisms which are not manipulative, have one's best interest in mind, and aid towards one's goals.

Preference change: A framework

The field of preference research is in need of a theoretical framework that can pinpoint the elements that have an effect on preferences and establish the relationships between them. Rather of providing a laundry list of variables, the suggested framework explains how these factors interact with one another to influence preference shifts. Figure 1 is a visual representation of our suggested framework.

Preferences are shaped by behavior, capacity, and decision architecture, according to the framework. All conative mental states, whether reflective or automatic, are operationalized by the aforementioned concept of preference. Because conative states are inherently affected by environmental factors, the concept posits that decision architecture influences preferences (Michie et al. 2014). On average, individuals will choose activities (and related tasks) that are simpler for them to undertake, which is impacted by their competence (Lee and Benbasat 2011; Juvina et al. 2018). In conclusion, behavior and preference are in a two-way causal connection, often referred to as a feedback loop (Albarrac'ın and McNatt 2005; Ariely and Norton 2008; Wyer Jr, Xu, and Shen 2012; Hill, Kusev, and Van Schaik 2019). While preferences can influence action, it is more common for conduct to precede and even initiate the development of new preferences.

Performing actions in response to stimuli from one's immediate surroundings is what we call behavior (Popescu 2014). Depending on the situation, it is operationalized differently. In addition to the preference-behavior link discussed earlier, behavior also has a causal relationship with capacity and choice architecture that goes in both directions. Research by Billitt (2010) and Vaci et al. (2019) shows that behavior affects capacity, which in turn results from practice and learning. Studies have shown that individuals will typically stay away from things that they perceive as mentally or physically taxing, providing further evidence that capacity influences behavior (Kool et al., 2010; Feghhi and Rosenbaum 2021). If you want to enhance a certain behavior in a population, make it easy for people to perform it. This is an idea that behavior change practitioners apply (Halpern 2015). Finally, decision architecture has been shown to have a significant impact on behavior in behavioral science studies (Michie, Van Stralen, and West 2011; Thaler and Sunstein 2021). When people act in a certain way, it modifies that environment.

Abilities are defined as people's mental or physical capacities, in line with the COM-B model (Michie, Van Stralen, and West 2011). Changes in performance serve as the operationalization metric for capability. Knowledge, memory, attention, behavioral control, cognitive abilities, and willpower are all examples of psychological abilities (Atkins et al. 2017). Strength, stamina, and the ability to do a variety of activities are all examples of physical talents. Ability is causally affected by choice architecture in addition to the previously mentioned relationships with desire and behavior. Land and Jonassen (2012), Gilavand (2016), and Amundrud et al. (2021) found that different contexts encourage different levels of skill acquisition. Boosts, which are behavioral treatments that enhance people's skills, are used to capture these insights in behavior change (Franklin, Folke, and Ruggeri 2019; Hertwig and Gru¨ne-Yanoff 2017).

The current framework conceptualizes choice architecture according to its original meaning, which was put out by Thaler and Sunstein in 2008. According to Thaler, Sunstein, and Balz (2013), the setting in which individuals act is known as choice architecture. In contrast to COM-B, which only makes use of choice architecture in its later iteration, the current framework incorporates both opportunity and choice architecture in its current form (Michie, Van Stralen, and West 2011). Thus, the current framework's choice architecture records the resources provided by the social (e.g., language) and physical (e.g., time and place) environments for a behavior. Additionally, it records elements of the social and physical surroundings that impact changes in preference, behavior, and capability. Different parts of the environment have bigger or lesser impact sizes, meaning they are not all equally significant. An exhaustive examination of the many physical environment factors that have been shown to have an impact is outside the purview of this study (Ruggeri 2018; Thaler and Sunstein 2021). According to Cialdini and Goldstein (2004) and Cialdini and Griskevicius (2010), the social environment may have an impact on an individual's behavior via other people's actions or their expressed preferences. According to Reno, Cialdini, and Kallgren (1993), in the field of behavioral science, these factors are known as descriptive social norms, which dictate how the majority of people act, and injunctive social norms, which indicate what the majority of people value and favor.

Where to take the field in the near future

Psychologists, cognitive scientists, computer scientists, marketers, economists, philosophers, and lawyers may all contribute to a stronger science of choice by drawing on their respective areas of expertise. It would be advantageous to do translational research that makes use of current knowledge in these areas. We may learn more about preference change, meta-preference, and preference-changing preference if this kind of study were to broaden the definition of choice.

Additional empirical and simulation investigations could enhance preference science. The development of preference-centered paradigms that investigate the predictive power of ability, behavior, and decision architecture changes in preference is a necessary step in this direction. Researchers may also test theories using simulation experiments that use acceptable assumptions for preference change processes.

Businesses with access to user data and the means to quickly implement interface improvements are well-positioned to undertake preference-science studies in-house. Even in a commercial setting, research that may be classified as behavioral experimentation must adhere to the established ethical and legal guidelines. In order to ensure that any study undertaken behind closed doors is morally and legally valid, it is imperative that computer engineers educate themselves on the topic of user manipulation and include it into their academic curriculum. This can only occur if Preference Science clarifies the circumstances under which altering one's preferences is both morally and legally acceptable. A significant contribution of this study is the idea that changing user preferences always involves thinking about ethics.

Conclusion

The fact that owners of AI and ML systems are manipulating user preferences for personal gain is the impetus for this article's call for an interdisciplinary research of preference change processes. This is often achieved by using strategies to alter one's behavior. After introducing a general concept of preferences, we went over the key points of meta preferences and preference-change preferences. We bring forth a model that examines the ways in which preferences are shaped by the ever-changing relationship between decision architecture, capacity, and action. We contend that in order for society to distinguish between legitimate and harmful preference change activities, legal and ethical frameworks are necessary.

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