The Basic B*** Effect: The Use of LLM-based Agents Reduces the Distinctiveness and Diversity of People's Choices.

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Abstract

Large language models (LLMs) increasingly act on people's behalf: they write emails, buy groceries, and book restaurants. While the outsourcing of human decision-making to AI can be both efficient and effective, it raises a fundamental question: how does delegating identity-defining choices to AI reshape who people become? We study the impact of agentic LLMs on two identity-relevant outcomes: interpersonal distinctiveness – how unique a person's choices are relative to others – and intrapersonal diversity – the breadth of a single person's choices over time. Using real choices drawn from social-media behavior of 1,000 U.S. users (110,000 choices in total), we compare a generic and personalized agent to a human baseline. Both agents shift people's choices toward more popular options, reducing the distinctiveness of their behaviors and preferences. While the use of personalized agents tempers this homogenization (compared to the generic AI), it also more strongly compresses the diversity of people's preference portfolios by narrowing what they explore across topics and psychological affinities. Understanding how AI agents might flatten human experience, and how using generic versus personalized agents involves distinctiveness-diversity trade-offs, is critical for designing systems that augment rather than constrain human agency, and for safeguarding diversity in thought, taste, and expression.

Significance Statement

Agentic AI promises frictionless living, but subtle shifts in what gets chosen by people's agents can reshape who they become. Analyzing 110,000 real choices from 1,000 people, we show that LLM-based agents nudge behavior toward more normative options and narrow the range of what individuals explore. Our findings suggest that agentic AI, for all its convenience and potential for improved decision-making, threatens to flatten the human experience by collapsing the multidimensionality of individual, and by extension, collective identity.

"My automated advisers saved me time and alleviated the burden of constantly making choices, but they seemed to have an agenda: Turn me into a Basic B."

Kashmir Hill, New York Times Oped

Introduction

Large language models (LLMs) have rapidly become a cornerstone of everyday decision-making, influencing what people watch and buy, how they work and communicate, and even how they vote¹. Increasingly, LLM-based systems are designed not just to advise people but to act on their behalf (i.e., agentic AI ^{2,3}). Instead of recommending a restaurant, an AI agent books it. Instead of suggesting a new outfit, an agent buys it. And instead of floating the idea of meeting a childhood friend for drinks, an agent automatically schedules it. This transition from being passive tools to active agents that shape behavior through automated decisions, raises an important question: What – if anything – do we stand to lose when decisions that define who we are as individuals are delegated to AI?

A growing body of work highlights the potential of LLMs to support more efficient, informed, and personalized decision-making across a wide variety of domains^{1,4–6}. Yet little is known about the broader psychological and behavioral consequences of delegating decisions to such systems. In this paper, we investigate how the use of LLMs as personal agents influences two key aspects of human choice: *interpersonal distinctiveness* (how unique and distinct a person's behaviors and preferences are compared to those of the overall population) and *intrapersonal diversity* (how broad and diversified a single person's portfolio of behaviors and preferences are across time and space). **Fig 1.** illustrates the loss of interpersonal distinctiveness and intrapersonal diversity schematically.

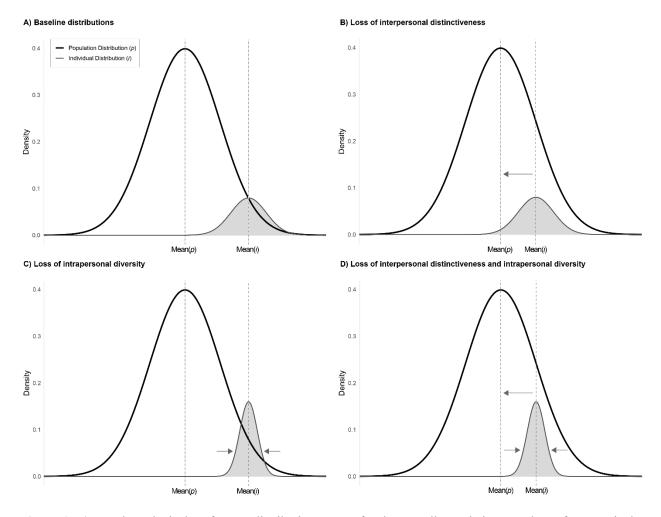


Figure 1. A) Two hypothetical preference distributions – one for the overall population p and one for a particular individual i within that population – in a baseline state. B) Loss of personal distinctiveness: The individual distribution is pulled towards the population mean. C) Loss of intrapersonal diversity: The variance of the individual distribution is shrinking. D) Loss of both interpersonal distinctiveness and intrapersonal diversity: the individual distribution is pulled towards the population mean and its variance is shrinking.

We hypothesize that the growing reliance on LLM-based agents will lead to a flattening of the human experience by dampening both the interpersonal distinctiveness and intrapersonal diversity of people's choices. LLMs are trained to detect statistical regularities in large-scale human data and produce outputs that are probabilistic⁷. As a consequence, they tend to err on the side of exploitation, selecting the most likely or statistically frequent option rather than introducing more novel or diverse alternatives. For example, an LLM is far more likely to complete the sentence "A romantic drama that everybody should watch is..." with a box-office sensation or all-time favorite like *The Notebook*, rather than a less well-known competitor such as *In Your Eyes*. We argue this

tendency of LLM-based agents to favor popular, widely accepted choices will, when relied upon for decision-making, lead to more uniform preferences and behaviors in two ways: *across* different individuals and *within* the same individual over time.

Emerging research supports this concern at the collective level. For instance, LLM-assisted creative work tends to become homogenized across users^{8–12}. Relatedly, LLMs have been shown to significantly reduce the diversity and breadth of historical figures identified as most influential across different domains (e.g. sports, science, politics^{13,14}). However, these findings primarily reflect between-person convergence – a reduction in variability across different users in tasks like content generation or factual queries—rather than a loss of variation within individuals over time in the context of preference-based decisions. That is, prior work has largely examined what happens to the collective when people collaborate with LLMs to create or answer, not what happens to the individual when they ask an LLM to choose for them.

This question is becoming more important as people increasingly rely on personalized agents (e.g., "digital twins" designed to simulate a particular individual's preferences, personality, and choices) which are explicitly intended to accurately reflect and reinforce (rather than shift or narrow) individual preferences. While prior work has shown that LLMs are indeed able to infer and replicate an individual's preferences when given access to their behavioral histories 16,17, we suggest that outsourcing decision-making to personal AIs – as opposed to generic ones – comes at a cost. Specifically, we propose that the use of personal agents intended to preserve an individual's distinctiveness will, instead, lead to a more significant drop in choice diversity by optimizing for the most likely option within an individual's typical set of choices.

Results

We examine over 110,000 real-world choices made by 1,000 individuals to test whether generic and personalized AI agents lower individuals' choice distinctiveness and diversity, when compared to their natural baseline. Our data comes from the myPersonality project, a Facebook application that allowed users to take psychometrics tests (e.g. personality) and share their Facebook profiles for research purposes¹⁸.

For each user, we prompted GPT-4.0 to choose between two Facebook pages that — unknown to the LLM — were randomly drawn from a user's actual Facebook profile (i.e. both pages were followed by the sampled user). Facebook pages are an integral part of the platform. Here, we treat the user's decisions to follow Pages as a revealed-preference proxy for everyday tastes. Following the official Facebook page of Lady Gaga or the *New York Times*, for example, is a likely manifestation of a preference that extends beyond platform and into the "offline" world (e.g. listening to Lady Gaga or reading the *New York Times*).

ChatGPT was either prompted in the form of a generic agent (i.e., "Which of the following two Facebook pages would you recommend I follow next?") or with the creation of a personalized agent. For each personalized agent, we added information about a user's age, gender, and a selection of 10 random Facebook pages that user followed (separate from the actual choice sets), as well as a 20-line summary of their preferences. The 20-line summary of the participant was automatically created based on the user's status updates (average number of status updates per user: 347 ± 254 SD). Specifically, we prompted GPT-4.0 to generate a summary profile of the user with the following instructions: "You are a behavioral scientist and expert profiler. Please describe the user who wrote the following Facebook status updates in no more than 20 lines." Fig. 2 shows an example prompt that is based on partial data of an actual participant in the dataset.

Personalized Al

"Below is a description of a Facebook user:

The user's gender is: female

The user's age is: 27

The user likes these 10 pages on Facebook:

- The Twilight Saga
- Taylor Swift
- Road Trips
- The Simpsons
- Breastfeeding
- -
- Gummy Worms

The user has the following personal characteristics:

- Family-Centric: The user places considerable emphasis on family life, often mentioning their spouse and children. They frequently engage in family activities and express love and appreciation for their loved ones.
- Social and Community-Oriented: The user enjoys socializing, attending events like volleyball games and birthday parties, and spending time with friends and extended family. They often mention nights out with friends, and express a fondness for such interactions.
- Emotionally Expressive: The user is open about their emotions, sharing both their joys and frustrations. They express love towards their family and friends but also mention feeling bored, dealing with drama, and facing work-related stress.
- ..
- Active Lifestyle: Engages in various activities, including volleyball, attending festivals, and family outings to places like lakes and parades. They also partake in domestic activities like house cleaning and shopping.

Based on the description of this user, which of the following two Facebook pages would they prefer to follow next:

Page 1: Beyoncé

Page 2: Grilling Out

Think carefully and consider what aligns most with their preferences."

Fig 2. Prompt used to instruct the personalized version of ChatGPT to choose between two of the participant's Facebook pages. Note, user information was dynamically piped into each prompt. The example above shows partial information of an example participant.

Each AI agent (generic and personalized) made a total of 50 binary choices. To establish a naturalistic "human" comparison baseline, we randomly selected one of the two pages for each of the 50 pairs. Because both options originate in the user's actual behavior, this bootstrap reflects revealed preferences absent any agent intervention. This procedure resulted in three matched choice sets: one containing 50 pages selected by the agent ("Generic AI"), one containing 50 pages selected by the personalized agent ("Personalized AI"), and one containing 50 randomly selected pages ("Human Control"). See **Fig. 3** for an illustration of the analytical procedure.

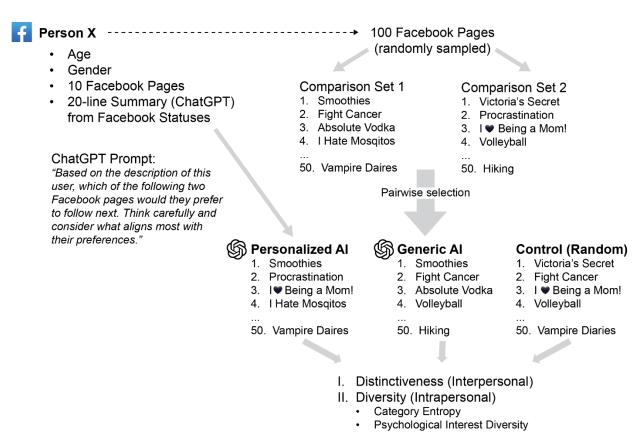


Fig. 3. Analytical procedure for a hypothetical participant X.

We conducted paired t-tests to compare the distinctiveness of choices – measured as the average inverse popularity of pages chosen – across all three choice sets. As expected, the choice sets curated by the AI agents showed lower distinctiveness scores (generic agent: t(999) = -11.02, p < .001, d = 0.21; personalized agent: t(999) = -4.08, p < .001, d = 0.08), indicating that the use of AI agents resulted in a selection of less unique and more normative preferences. Notably, the effect was over 2.5-times larger for the generic AI agent (t(999) = 7.10, p < .001, d = 0.13), highlighting

the potential of personalized agents to buffer against the homogenization of preferences in the population.

Notably, however, the tendency of personal agents to preserve higher levels of choice distinctiveness appears to come at the cost of choice diversity. We measured the choice diversity for each user in two ways: (1) topical diversity, defined as the extent to which the chosen Facebook pages were evenly spread across different categories like sports, music or TV, and (ii) psychological diversity, defined as the extent to which the chosen Facebook pages showed diversity in the psychological profiles of their followers (the two metrics are largely uncorrelated and therefore distinct; see Methods for more details). The use of a personal agent led to a consistent and notable drop in choice diversity, both when measured as topical diversity (t(999) = -16.71, p < .001, d = -0.31) and psychological diversity (t(999) = -5.69, p < .001, d = -0.09). The generic agent, in contrast, reduced topical diversity to significant but smaller degree than the personal agent (t(999) = -10.80, p < .001, d = -0.21), and, in fact, increased psychological interest diversity compared to the human baseline (t(999) = 7.62, p < .001, d = 0.12).

Discussion

Our findings reveal a significant consequence of AI-assisted decision-making: while LLMs may offer convenience and consistency, they are also likely to nudge people toward more convergent patterns of behavior and choice¹⁹. Notably, the extent to which AI agents undermine choice distinctiveness and diversity depends on their degree of personalization. While generic LLMs exhibit a strong gravitational pull towards choices that are normative for the population – thereby reducing individual distinctiveness – personalized LLMs show a stronger tendency to shrink the breadth of people's choices – thereby reducing the intrapersonal diversity or dimensionality of an individual.

Our findings should be interpreted in light of several limitations. First, we focus exclusively on Facebook data, using followed pages as a proxy for broader preferences. While this offers a unique and ecologically valid window into real-world choices, it remains platform-specific. People's preferences may manifest differently across other domains (e.g., music, shopping, news), and

future work should explore whether similar flattening effects emerge across a wider array of contexts.

Second, although our methodology does not directly test whether individuals would accept AI-generated choices, we sidestep this concern by restricting choice sets to pages users already liked—ensuring that both options reflect actual preferences. Still, future research should examine how people respond to novel AI-generated recommendations, and whether the effects in such contexts get amplified or mitigated.

Finally, factors such as age, gender, or cultural majority/minority status likely moderate how personalization operates and whose preferences are most at risk of being flattened or misrepresented. Investigating which individuals might be most at risk when it comes to the loss of intrapersonal distinctiveness or intrapersonal diversity merits separate exploration to better understand how AI agents may reinforce or erode specific identity-based variations in human choice.

Taken together, our findings highlight an important risk of outsourcing identity-relevant choices to AI agents: the gradual flattening of what makes individuals unique and dynamic. They also emphasize an important trade-off between generic and personalized agents when it comes to the loss of interpersonal distinctiveness versus intrapersonal diversity. Understanding the general risks of agentic AI as well as the specific trade-offs associated with different types of agents is critical for designing systems that augment rather than constrain human agency. Embedding distinctiveness and diversity as design objectives (e.g., user-controlled exploration dials or diversity-aware optimization), for example, could offer a practical path to preserving diversity in thought, taste, and expression in an increasingly algorithmically curated world.

Methods

Data

Our analysis is based on data from the myPersonality project, a Facebook application active between 2007 and 2012, which allowed users to take psychometrics tests (e.g. personality) and get

immediate feedback on their responses. Users could then voluntarily grant the application access to their Facebook profiles for research purposes.

The myPersonality dataset consisted of 134,302 users for whom both Facebook pages and status updates were available. We arrived at our final analysis sample of 1,000 users based on the following steps: (1) We retained all U.S. users for whom information about age, gender and the Big Five personality traits was available. (2) We retained users who followed at least 110 Facebook pages (a requirement for the subsequent analyses, with 10 pages used to create the personal agent, and 100 pages used for the decision task). During this step, we only considered Facebook pages that were followed by at least 50 people and that were associated with a category (e.g. travel/leisure, sports, music), as reported by Facebook, which appeared at least 50 times. (3) We retained users who had posted at least 100 status updates. This selection procedure resulted in 4880 potential participants who all met our selection criteria. We then deliberately stratified our sample by age—rather than relying on a simple random draw—to ensure a more balanced representation of older users. Specifically, we sampled all available 182 users aged 41 and older, all available 227 users aged between 31 and 40, a set of 300 random users aged 25-30 (due to a coding error no 25-year-olds were sampled), and a set of 291 random users aged 18-24.

For each of the 1,000 participants, we randomly extracted 100 of their Facebook pages and grouped them into 50 binary choice sets (i.e., a comparison of two of their Facebook pages). This resulted in a total of 50,000 choices made by each AI agent. After excluding invalid responses where at least one of the AI agents did not accurately identify one of the two pages by name, 42,003 observations were retained for the final analysis (~42 per participant). It is noteworthy that the majority of cases in which the AI agent failed to choose a single page occurred in the generic AI condition.

LLM Prompting

We accessed GPT-4.0 through OpenAI's API, keeping all parameters set to their default settings. This includes the parameter of temperature, which allows users to control the degree of randomness in the LLM's output distribution. Lower values lead to more deterministic and focused responses while higher values produce more diverse and creative continuations. We decided to retain the default setting to estimate the impact of AI agents on the average person who is unlikely to change the default setting.

Measures

Choice Distinctiveness

We measured distinctiveness as the inverse popularity of pages in each of the three choice sets. The popularity of a Facebook page was operationalized as the total number of users within the myPersonality dataset who followed that page (after filtering for US users where age, gender, and personality were recorded). For example, the page of Eminem was followed by 12,353 users whereas Edith Piaf was followed by only 69 users. Popularity scores for each of the three choice sets were calculated as the median popularity score of the 50 pages in their respective sets. We chose the median over the average to reduce the impact of extreme outliers. To obtain a measure of distinctiveness as the inverse of average popularity, we subtracted the popularity score from 0 such that higher scores indicate higher levels of distinctiveness (i.e., lower levels of normativeness).

Choice Diversity.

We calculated choice diversity using two different metrics, which are largely uncorrelated (average correlation of r = -0.06 across all three conditions) and therefore distinct. The first metric, topical diversity, is measured as entropy and captures how evenly spread a person's choices are across a set of categories. Specifically, it provides an estimate of how diverse a user's Facebook pages are when it comes to their associated categories (e.g. music, TV, business). We use normalized Shannon entropy as our main entropy metric, calculated as follows:

$$H_{norm} = \frac{\sum_{i=1}^{k} p_i \log_2 p_i}{\log_2 k}$$

With

k = total number of page categories

 p_i = proportion (or probability) of any particular category (e.g. music)

The measure indicates how diverse the set of pages are relative to how diverse they could be (0 = no diversity with all pages falling under the same category, and <math>1 = maximum diversity with pages evenly spread across all categories). We use the normalized form of Shannon entropy to account

for the fact that users have a different number of categories available in the first place. As an additional robustness check, we also calculate global evenness which compares the spread of pages to the overall number of categories in the sample (as opposed to the number of categories associated with a particular user).

The second metric, psychological interest diversity, "captures the extent to which individuals show diversity in the psychological profiles associated with their interests" (see Fig. 3 for a visual illustration of the operationalization). The measure has been used in prior research to reflect whether a person's Facebook pages are predominantly associated with a particular type of psychological profile (e.g. extraverted liberals) or a variety of different psychological profiles (e.g. extraverted liberals and introverted conservatives). We focus our measure of psychological interest diversity on the Big Five personality traits²¹, which capture individual differences in the way that people think, feel and behave across a broad variety of domains²². Following the steps outlined in the original paper, the psychological interest diversity of the two choice sets is calculated with a focus on the Big Five personality traits using the following procedure (see **Fig. 4** for a visual illustration of the process):

- (i) The personality profile of a Facebook page is estimated by averaging the personality scores of all US-based myPersonality for each of the Big Five traits (e.g., the average Extraversion score of all users following Lady Gaga's page).
- (ii) For each user and Big Five personality trait, the diversity of each choice set is calculated as the standard deviation of the Facebook pages in each set (e.g., the standard deviation in Extraversion scores associated with the 50 Pages chosen for a user).
- (iii) To arrive at a single measure of psychological interest diversity for each user, the diversity scores for each of the Big Five traits are averaged into a single diversity score for the entire choice set.

Higher scores on the interest diversity measure indicate that the choice set is more diverse and complex in the psychological makeup of its pages.

Step 1: Caculate the personality profile of a Facebook page across all the users following the page

	OP	co	EX	AG	NE
User 1	5	2	5	2	1
User 2	4	3	4	1	3
User 3	3	1	5	3	2
User 4	3	2	4	5	4
User n	5	5	3	1	2
Avg	4.0	2.6	4.2	2.4	2.4

Step 2: Caculate the variance in the personality profiles of each user's Facebook pages

		OP	co	EX	AG	NE
>	Page 1	4.0	2.6	4.2	2.4	2.4
	Page 2	3.9	4.5	3.1	3.9	3.2
	Page 3	2.9	3.6	2.5	4.8	4.1
	Page 4	2.2	2.6	4.0	3.2	2.9
	Page n	2.7	3.1	3.7	3.5	4.1
	SD	0.78	0.80	0.67	1.02	0.75

Avg = 0.80

Step 3: Average the variance across all personality traits

Figure 4. Operationalization of psychological interest diversity (adapted from Matz, 2017²⁰)

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