

The Algorithmic Crystal: Conceptualizing the Self through Algorithmic Personalization on TikTok

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This research examines how TikTok users conceptualize and engage with personalized algorithms on the TikTok platform. Using qualitative methods, we analyzed 24 interviews with TikTok users to explore how algorithmic personalization processes inform people’s understanding of their identities as well as shape their orientation to others. Building on insights from our qualitative data and previous scholarship on algorithms and identity, we propose a novel conceptual model to understand how people think about and interact with personalized algorithmic systems. Drawing on the metaphor of crystals and their properties, the *algorithmic crystal framework* is an analytic frame that captures user understandings of how personalized algorithms (1) interact with user identity by *reflecting* user self-concepts that are both *multifaceted* and *dynamic* and (2) shape perspectives on others encountered through the algorithm, by orienting users to recognize parts of themselves *refracted* in other users and to experience ephemeral, *diffracted* connections with groups of similar others. We describe how the algorithmic crystal framework can extend theory and inform new lines of research around the implications of algorithms in self-concept development and social life.

CCS Concepts: • **Human-centered computing** → **Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: algorithms, self-concept, crystallized self, folk theories, TikTok

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1 INTRODUCTION

Algorithms play influential roles in many aspects of people’s everyday experiences, including their professional, entertainment, financial, and social lives. Further, people often interface with algorithms in decision-making contexts that range from the next Netflix “watch now” click, to more consequential decisions, such as whether a particular job application is passed on to a human or ignored. However, not everyone is necessarily aware of algorithmic influence in all of these contexts [27, 29]. Even when they are, people are often left to speculate with various degrees of complexity [19] about what is happening inside the algorithmic black box.

Scholars have turned their attention to studying these speculations in recent years, as well as how these speculations influence other perceptions and behaviors. This is particularly crucial, as

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50 subjective understandings “are not second best to objective measures; in fact, it is perceptions and
51 subjective realities that people judge and act upon” [67]. Perceptions of algorithms can be shaped by
52 individuals’ lay theories about their functioning and knowledge about the technical processes that
53 underpin personalization (e.g., algorithmic literacy) [25, 43]. Further, because algorithms change as
54 a result of the data input they receive in a kind of feedback loop [50, 55], Bucher [9] even argues
55 that these perceptions can then influence the nature of the algorithms themselves. Indeed, Karizat
56 et al. [38] refer to this phenomenon as a process of co-production, in which people may influence
57 algorithmic output, but algorithmic output may also influence people’s perceptions.

58 A great deal of scholarly attention has been paid to TikTok in particular as the platform has
59 grown in popularity (e.g., [2, 5, 40, 65]). The For You Page (FYP) is of particular relevance, as it is the
60 first feature of the platform that users interface with, and involves algorithmically-curated videos
61 purportedly based on users’ interests. In the current study, we aim to understand how TikTok users
62 think about the FYP algorithm as it relates to their identity. We focus on the idea of self-concepts
63 [44] to describe the many identities, roles, beliefs, and values that compose an individual.

64 In addition to potentially emphasizing relationships between perceptions of the algorithm and
65 perceptions of the self, TikTok also affords strangers as the main audience for one’s content [4].
66 Instead of direct interactions with networks of known ties, Zulli and Zulli [77], as well as Abidin
67 [2], suggest that social media platforms like TikTok afford a different kind of social experience. As
68 such, people’s self-concepts may be particularly salient in terms of how they perceive others on
69 the platform. As such, we ask the following:

70
71 *RQ: How do participants perceive the algorithm in relation to their self-concept?*
72

73 We conducted semi-structured interviews with 24 self-reported active TikTok users. The results
74 of this study suggest that our participants recognized parts of their identity in the FYP algorithm’s
75 content recommendations. Subsequently, they felt a desire to bring algorithmic representations
76 of themselves into alignment with their own self-concepts. Participants felt that their behaviors
77 could shape the algorithm’s ability to accurately reflect their multifaceted and dynamic interests
78 and preferences. Further, the algorithm facilitated feelings of “mere belonging” towards others on
79 the platform, with multiple participants reporting positive feelings toward others even though
80 little to no interpersonal interaction took place. We synthesize our results with prior literature on
81 algorithmic interactions and self-concepts, and introduce an analytic framework - the *algorithmic*
82 *crystal framework* - that coalesces our findings and can help guide future work.
83

84 1.1 Related Work

85 One way to approach investigating perceptions of algorithms and the sociotechnical systems in
86 which they operate is by exploring algorithmic folk theories, or “intuitive, informal theories that
87 individuals develop to explain the outcomes, effects, or consequences of technological systems,
88 which guide reactions to and behavior towards said systems” [21]. Although these folk theories
89 are developed with varying levels of awareness of algorithmic capabilities [19], they can shape
90 people’s behaviors on platforms, which in turn can be treated as input data for the algorithmic
91 decisions themselves. A dominant algorithmic folk theory is that of Personal Engagement [25],
92 in which people anticipate that the more they interact with a specific type of content, the more
93 they would see similar content on their algorithmically-curated feed. In a general sense, many
94 algorithmic systems that determine the content that users are exposed to actually work in this way
95 as well [62]. Overall, algorithmic folk theories can be considered a collection of perceptions about
96 algorithms that influence peoples’ behavior when interacting with these systems.
97
98

99 Other scholars have investigated perceptions of algorithms from different lenses [52, 53]. For
100 instance, Bishop [7] examined “algorithmic gossip” or how people talk about their algorithmic in-
101 teractions with others. This is especially prominent among content creators; through this discourse,
102 content creators may change their behaviors in order to achieve goals like gaining visibility on a
103 certain platform. Relatedly, Siles et al. [56] also approaches perceptions of algorithms from a more
104 pluralistic sense. These authors argue that it is through people’s collective algorithmic imaginaries,
105 or “ways of thinking about what algorithms are, what they should be, how they function and
106 what these imaginations in turn make possible,” [9] that large scale changes in human-algorithm
107 interactions can be enacted. Although these concepts highlight various mechanisms through which
108 scholars can better understand interactions between humans and algorithms, they converge by
109 focusing on perceptions of these technologies, and how these perceptions may influence behavior.

110 In particular, the role of identity in algorithmically-curated interactions has been a prominent
111 area of investigation, especially on the TikTok platform (e.g., [6, 38, 41, 59]). For instance, some
112 TikTok users perceive that the “algorithm recogniz[es], classifi[es], sort[s], and suppress[es] social
113 identities” on the platform, replicating extant gender-based or racialized power dynamics present
114 outside of TikTok [38]. Indeed, popular media has also reported on user experiences related to
115 thinking about the self, speculating that the videos shown to users say something about the type of
116 person they are [68], or even allow users to better understand their own identity [8, 45].

117 Researchers have often examined self-concepts - or the the many identities, roles, beliefs, and
118 values that compose an individual [44] - on social media as they are demonstrated through
119 self-presentation (e.g., [12, 64, 72]). Recently, Simpson and Seeman [59] have investigated how
120 algorithmically-curated content can both affirm and violate notions of one’s own identity, especially
121 in the case of users with marginalized identities (e.g., LGBTQ+ users). French [28] also found similar
122 effects, even indicating that people’s perceptions of themselves may change based on information
123 provided by an algorithm. In the case of TikTok, Bhandari and Bimo [6] argue that because users
124 overwhelmingly engage with a “personalized algorithm which repeatedly confronts users with
125 various aspects of their own personas” called the For You Page, the processes of self-perception
126 may interact with platform affordances in unique ways and rely on different mechanisms than in
127 previous research on the topic.

128 Since the affordances on a platform can allow, or even encourage or discourage, various behaviors
129 [18], people’s experiences on TikTok may be shaped by what features are or are not available. Even
130 though other platforms such as Twitter or Reddit allow interactions with strangers, for instance,
131 the visual salience of the content creator is not highlighted in the same way it is on video-based
132 platforms like TikTok [42, 77]. Further, the aforementioned algorithmically-curated FYP is arguably
133 the most salient feature on the platform. As such, “network form[ation] through processes of
134 imitation and replication” [77] in terms of visual content is common, meaning that users do not
135 necessarily need to have direct social interactions with others to form connections. The networks
136 of content connected by similar algorithmically-curated content on TikTok have been discussed as
137 “rabbit holes,” “silos” and “subcultures” [1], as well as “sides” [24]. TikTok does allow the formation
138 of interpersonal networks with the ability to follow one’s known ties or direct-message others.
139 However, predominance of the FYP, combined with the visual salience of the content creators, is
140 in notable contrast to many popular social media platforms which rely heavily on content from
141 known ties in a network, rely less on visual content, or both.

142 The lack of direct, interpersonal connections between platform users may mean that how people
143 think about others, specifically in relation to themselves, has the potential to be particularly salient.
144 Further, the ways in which algorithmically-curated content interacts with perceptions of the self
145 may be especially notable as well, as recent researchers have also noticed. In this paper we examine
146
147

148 how TikTok users perceive the FYP algorithm, particularly in the context of personalized content,
 149 as well as how perceptions of the algorithm influence beliefs about the self.

151 2 METHOD

152 2.1 Participants

153 Our sample consisted of 24 students recruited from three universities in California, two community
 154 colleges (n = 13) and one private university (n = 11), in order to increase the potential for diversity
 155 in our sample. They were recruited through an online participant recruitment system called Sona
 156 to take part in a “TikTok Study.” Sona is an online scheduling service used by the universities to
 157 manage their research participant pools. By signing up to take part in our study on Sona, students
 158 attending these universities can complete research studies in exchange for research credits, which
 159 are a required component of their social science classes. We stopped recruiting participants after
 160 achieving saturation, or when we started hearing similar ideas from participants [15]. Participants
 161 were required to be 18 years or older and active TikTok users in order to be eligible to participate.
 162 We allowed participants to interpret the term “active” however they wished. The average age of
 163 participants was 23 years old (range: 18 - 43). The majority of participants identified as female (n =
 164 18; male, n = 6). Our sample included 11 participants identifying as Hispanic/Latino, 8 as White, 4 as
 165 Native American/Indigenous, 4 as Asian/South Asian, and 1 as Black/African American, with some
 166 identifying with multiple identities. The majority of participants were heterosexual (73.9%), with 1
 167 identifying as queer, 1 as bisexual/pansexual, 1 as bisexual, 1 as undecided, and 1 who declined
 168 to respond. In order to protect the privacy of participants in our relatively small participant pool,
 169 we report the demographic information in aggregate above, as opposed to in an individualized
 170 manner in Table 1. All participants received research credit, part of a course requirement, for their
 171 participation.

173 Table 1. Self-reported participant demographic information

Participant	Age	Gender	Participant	Age	Gender
P1	22	Male	P13	19	Female
P2	22	Male	P14	20	Female
P3	21	Female	P15	18	Female
P4	21	Female	P16	18	Male
P5	20	Female	P17	24	Female
P6	18	Male	P18	25	Female
P7	19	Female	P19	30	Female
P8	24	Female	P20	22	Female
P9	20	Female	P21	43	Male
P10	20	Female	P22	31	Male
P11	21	Female	P23	24	Female
P12	31	Female	P24	27	Female

191 2.2 Procedure

192 Data collection consisted of interviews that were conducted remotely using the video-conferencing
 193 platform Zoom due to the COVID-19 pandemic. The interview protocol was developed by the
 194 research team in order to provide opportunities to explore users’ perceptions, engagement, and
 195 reasoning about the TikTok platform. All interviews were conducted in a semi-structured format

197 to allow researchers to explore and probe participants' perspectives. The final protocol consisted of
198 32 open-ended questions that asked about participants' perceptions and attitudes about the TikTok
199 app (e.g., How would you describe TikTok? How do you tend to use it?), their understanding of
200 the different types of content (How would you describe the content you see on TikTok?), and how
201 they understood the functioning and characteristics of the algorithm (How would you describe
202 the TikTok algorithm if it were a person?). We also asked participants to report demographic
203 information about their age, gender, race and ethnicity, and sexual orientation at the end of the
204 interview, with all participants having the option to not answer any questions. This study was
205 approved by the IRB at the first authors' university.

208 2.3 Research Positionality Statement

209 Some of the identities represented in our research team included woman of color, immigrant, and
210 first-generation college student. Our team includes experts in social media, algorithms, and folk
211 theorization.
212

214 2.4 Data Analysis

215 Interviews were conducted remotely by the first authors from February through May 2021. The
216 interviews were recorded using the record-to-computer feature on Zoom with participants' consent,
217 and the audio was transcribed using an automated online transcription service (Otter.ai). The
218 first authors removed identifying information from the transcripts, assigned all participants an ID
219 number (e.g., P1, P2), and flagged instances of technical errors in the recordings (e.g., from poor
220 Internet connection). All transcripts were checked for accuracy twice, first by one of four research
221 assistants and then by the first authors. The checked transcripts were imported into the qualitative
222 coding software ATLAS.ti for analysis and coding. Quotes included in the manuscript were lightly
223 edited for clarity.
224

225 The first authors generated an initial list of in-vivo codes, using phrases from participants
226 themselves (e.g., the "relatable" quality of other users) which were iteratively reviewed and discussed
227 by the research team. Example codes included feeling "seen" by the algorithm, feelings of control
228 over the algorithm, and the diversity or similarity of content identified by the algorithm.

229 New axial codes were added to the codebook throughout the coding process to capture new
230 insights and to identify higher-order themes (e.g., strategic engagement with the algorithm) [73].
231 Example codes included lay or folk theories about the algorithm's functioning, perceptions of the
232 algorithm (e.g., as a person), and signals of algorithmic personalization. Throughout this process,
233 we wrote research analysis memos [46] where we identified key themes that emerged from the
234 qualitative coding and review process, exemplar quotes, and questions for discussion with the
235 research team. Materials including the full interview protocol and list of codes are available upon
236 request from the corresponding author.

237 In addition, we created a data matrix to identify higher-level patterns at the participant level
238 [46]. For example, we classified participants by their degree of reported perceived personalization
239 of the TikTok For You algorithm, their sense of belonging or engagement with TikTok groups or
240 "sides," the amount or intensity of their TikTok use, and whether they created content for TikTok
241 or predominantly consumed it. Using this matrix, we were able to organize our observations of
242 individuals' perspectives on the algorithm around individual differences, such as users' preferred
243 method of engagement or the amount of their use.
244

3 FINDINGS

3.1 The Algorithm Knows Me Well: Reflecting Multifaceted and Dynamic Self-Concepts

We examined how individuals theorized about the relationship between the algorithm and their sense of self-concept. As other research has observed (e.g., [25, 57]), some participants evaluated the algorithm more positively when it offered them relevant or personalized content. The majority of participants, particularly those who were heavy or frequent TikTok users, believed that the algorithm learned who they were and what they liked by analyzing traces of their behavior. Prior work has discussed this kind of theorizing as an algorithmic folk theory of personal engagement [25]. While some participants expressed uncertainty and curiosity about how the algorithm worked, many perceived their experiences as the algorithm attempting to understand and reflect them.

Specifically, some participants emphasized the importance of the algorithm's ability to recommend content in line with a sense of self-concept that they viewed as fundamentally *multifaceted* and *dynamic* - two characteristics we discuss in turn below. Based on our analyses, we found that participants noted that they had varying identities and interests, some of which remained relatively stable and constant over time (nationality, native language, a life-long passion for theater, etc.), and others that were more likely to evolve or change (photography, nature, baking, or a particular TV show, etc.). How good an algorithm was perceived to be, then, was a function of its sensitivity: the algorithm's continuous "tailor[ing]" or "mold[ing]" to the set of facets that comprised users' self-concept (P4, P10, P15), resulting in a feeling one participant described as the algorithm "know[ing them] so well" (P10).

Many tended to value moments when the algorithm seemed to reflect many different facets of themselves. Rather than providing recommendations for only one or two key interests, the TikTok algorithm was described as "tailored to everything you'd want to see and be entertained by" (P14) and "showing me everything, like everything from the corners of my mind" (P8). For example, one participant (P13) enthusiastically attributed her enjoyment of TikTok to the diversity of content recommendations that spoke to her many specific interests, commenting that "it's nice that they all blend into [a] customized page for me." Having described herself as being passionate about education, pets, theater, horse videos and Vine-like humor, among other topics, she said:

"It doesn't take long for [TikTok] to calculate what videos I watch, what videos I don't watch, what my engagement is. So it just becomes more and more specific the more I use it. I don't see how it can get any more specific, like it's pretty insane how accurate it is right now."

As demonstrated by the above quote, the specificity of the algorithm was determined by its ability to aggregate and recommend content that reflected the many and multiple facets of participants' self-concept. The "insane" accuracy of the algorithm, then, was about creating a unified blend of customized content recommendations that reflected users' diverse interests and identities into a single stream. It was not enough for the algorithm to provide highly specific recommendations for one particular interest, which could be interpreted as the algorithm producing a reductive representation of the self. For example, one participant (P14) preferred TikTok's algorithm over the Instagram Explore page because they thought it was better at capturing the multifaceted nature of their personal interests:

"With the Instagram Explore page, I feel like there's so much less variety, like if you click on a specific kind of post more than [once], it'll just give you a lot of that same post. Whereas with TikTok, I feel like the selection is so much larger... Even while tracking what you're more likely to enjoy or view... it's still a much wider selection of different kinds of content, or different kinds of styles of posting or different trends."

In addition to being multifaceted, we observed that most participants tended to view themselves and their interests as changing over time - or as being dynamic. Thus, they wanted the algorithm to be responsive and rapidly update its representation of the user's self-concept. For example, the TikTok algorithm was seen as better than others that were perceived to be more stagnant, which caused some people to feel constrained by older identity elements and outdated preferences and thus typecast as one-dimensional. For example, one participant (P13) described TikTok as being able to "catch on to what I like, almost immediately" whereas the Instagram algorithm "took a long time to catch up to what I like":

"[My Instagram Explore Page] has not updated in the slightest, no matter how many times I will 'like' different things or whatever. I had a huge Disney phase, it's all Disney stuff on my Explore page, and I'm so sick of it. So just that fact alone is making me use it even less and less."

In this quote, we can see that the participant felt "sick of" the Instagram Explore page algorithm because it was recommending content for an outdated version of herself that she no longer identified with. Being shown a reflection of her former self as an avid 16-year old Disney fan by the algorithm felt uncomfortable and frustrating. As demonstrated in the above example, the discontinuity between one's current self-concept and an algorithmic representation of a previous self can create a sense of temporal dissonance in identity, especially when differences between past and present selves are salient - which might be particularly relevant for emerging adults [3] transitioning from Disney-fan childhood to adulthood.

However, this does not mean that participants wanted the algorithm to continuously start from scratch when attempting to reflect their current interests. A common theme we observed across participants was a tension between wanting the algorithm to cater to past interests, while also being receptive to new interests and creating opportunities for personal growth and new discoveries. Although some participants expressed that they did not want the algorithm to concentrate on specific interests, others pointed out that they valued when the algorithm was able to remember former interests and rotate through a combination of former and newer interests in a way that they described as "time-shifting" (P2). As one participant explained, she felt that her experience with TikTok involved "never staying on one [interest area] for long," but rather that her feed "goes through a cycle" (P13). For example, she appreciated when the algorithm appeared to remember that she enjoyed watching videos from Frog TikTok; even if frog videos had not "come up for a while" on her feed, she felt confident that it would come back up again eventually. Another participant (P2) voiced a similar sentiment, saying:

"And I think that kind of goes back to the algorithm too... There's a lot of people that like to talk about a specific thing, and that obviously shifts over time. But there are certain communities probably that persist over time, whether it's about elections... there'll always be that community of posts that you can probably find if you like something or look at a profile that has something like that."

Together, these findings suggest that people understood personalization processes in the FYP as the algorithm trying to develop an accurate representation of their self-concept, preferably in a way that captured their multifaceted interests and dynamic ability to change over time. At a high level, we observed that some users believed the algorithm could know their "their true self" because it was capable of identifying content in line with the contours of their identity.

3.2 Aligning the Algorithmic Self with the Actual Self

In addition to evaluating how well the algorithm's representation of them fit with their self-concept, almost all of our participants had a working understanding that the algorithm's representation of

344 them was shaped by their everyday use of the app, such as the videos they watched and the content
 345 they engaged with. Whereas previous work on algorithmic selves has highlighted that there are
 346 various degrees of user awareness of how their data are represented through datafied systems [11],
 347 our findings indicate the potential for users to not only be aware that this personalization process
 348 is occurring, but also to want to bring their algorithmic self into alignment with their actual self.

349 One way some participants thought they could shape the algorithm was casual and unintentional:
 350 simply by being themselves and following their natural interests when engaging with content. Many
 351 reasoned that the algorithm could learn who they really were over time because it was making
 352 inferences from their everyday watching behavior, such as the number of times they watched the
 353 same video, whether or not they investigated a particular content creator, or if they skipped over a
 354 certain type of content (“I think I definitely enable it when I watch a video maybe twice... or if I
 355 look at the comments, or if I like it” - P5). Unlike other social media platforms with stronger norms
 356 around engaging with content to maintain social ties (e.g., feeling obligated to “like” a friend’s
 357 Instagram pictures [32]), the FYP algorithm could build an understanding of the user’s interests
 358 through content they organically gravitated to. While some participants saw this as producing
 359 quick, easy, and accurate representations of themselves, others felt like they had little control over
 360 what the algorithm learned in this fashion because it was like it was “read[ing] your mind” (P15).
 361 As one participant expressed, “It’s like he knows everything... the thing that we cannot control is
 362 definitely the AI” (P19). Thus, in this process, the algorithm’s representation of the self could be
 363 closely aligned with one’s actual self with little effort on the part of the user, but also difficult to
 364 evade or fabricate.

365 In contrast to these organic expressions of interest, another way that participants attempted to
 366 align the algorithmic self with their self-concept was more effortful and strategic. Some participants
 367 described feeling like they could shape what the algorithm learned by actively curating their engage-
 368 ment through deliberate interactions with the app. In this process, algorithms were valued when
 369 seen as responsive to bids from users to adjust its representations of them and recommendations for
 370 them. For example, several people described how these bids could be made explicitly by deliberately
 371 engaging with features to send a request to the algorithm (e.g., indicating they’re ‘not interested’
 372 by clicking on this option or saving the video):

373 *“If I really liked the video, and I want similar ones, it’s obviously liking the video or*
 374 *commenting, or adding it to my [collection of Favorited videos]. ... I know for videos*
 375 *[that] I don’t want to see... you can press the video and it’ll pop up like, a ‘not-interested’*
 376 *option... Sometimes I’m like, ‘No, I don’t want to watch this.’” - P9*

377 Users could also make bids implicitly by modulating their behavior in hopes that the algorithm
 378 would pick up on this change and thus learn to better model some facet of themselves. For example,
 379 in the context of describing her feed, one white participant (P18) described how she noticed that the
 380 algorithm was showing her videos of predominantly white creators and that she tried to deliberately
 381 change this by strategically engaging with Black creators:

382 *“Yeah I would say that at first I was probably seeing mostly white people... But again*
 383 *with BLM and everything - I started liking content by more Black creators and a more*
 384 *diverse set of creators.”*

385 We observed that people tended to make different attributions when they made a bid to the algorithm
 386 to change how it represented them. Some people felt they needed to do so because the algorithm was
 387 not sensitive enough to who they were, or that it was biased in its own way to showing particular
 388 content - which reflected poorly on their evaluation of the algorithm. A few participants, however,
 389 expressed a tension between their actual behavior and the kind of person they wanted to be. In
 390 this frame, they viewed the algorithm itself as highly capable of learning and modeling who they
 391

were, but felt uncomfortable about some of the identity facets that it brought to light. For example, this tended to involve content recommendations that indulged in interests that they viewed as unhealthy, such as snack foods. Seeing unsavory facets of oneself detected by the algorithm and reflected in its recommendations could spark a potentially discomfoting process of self-reflection and awareness.

Rather than viewing the algorithm as a purely mechanical function that recommended relevant content, we found that participants tended to anthropomorphize the algorithm to varying degrees. Some made sense of the personalization processes underlying the algorithm as being a “people-pleaser” (P22) that was capable of changing itself to be as similar to the user as possible. As one participant (P6) explained:

“It’s whoever you are. It’s like... the Pokemon that just turns into you. Or tries to. I mean, my TikTok experience is going to be completely different from someone else’s because [it] got so personalized to me so quickly... So the algorithm is just you. Or it’s just trying to be you.”

For participants like P6, the algorithm was viewed as a fundamentally malleable entity whose core mission is to transform itself into a copy of the user by learning to represent their interests and identities. However, people varied in how they thought about the goals of the algorithm in trying to learn and satisfy their tastes. For example, some participants viewed this in a purist, positive light, characterizing the algorithm as someone who enjoyed meeting their needs: “It would be someone who’s very obedient and very, like a people-pleaser. They like to accomodate for you” (P15). In contrast, others were more critical, viewing the algorithm’s motives for wanting to please them with more cynicism or apprehension. For example, one participant framed the algorithm as ensnaring, describing it as someone who “like, just wants to give you whatever you want” as a ploy to “keep you there [on the app] and not let you go” (P11). On the other hand, participants like P7 viewed the algorithm’s people-pleasing qualities as less malicious, but still hollow or insincere:

“It’s kind of like, if someone were to change their personality with everybody that they met in order to be - not necessarily the best person with the other person, but what they expect the other person would want, who they would want to hang out with.”

Despite these differing perceptions, however, people’s understanding of the algorithm appeared to be unified by a shared orientation to viewing the algorithm as attempting to represent themselves, with more or less fidelity. Overall, our findings suggest that people’s understanding of personalization processes shaped how they thought about the algorithm’s representation of themselves, why it was learning to form such a representation, and how to bring their algorithmic self and actual self-concept into alignment.

3.3 I’m Not the Only One: Algorithmic Exposure to Others on the Platform

Participants were able to experience a variety of sides, or subcultures [1, 24, 77] on their own algorithmically personalized feed, which contributed to an acknowledgement of themselves as complex, multifaceted, and dynamic. In comparison, they often had a more simplified, one-dimensional perception of others who happened to be on the same side as them. Rather than interacting with others on the platform through a conventional network of known ties and with direct interpersonal contact - like dyadic or group messaging on Facebook - our analyses suggested that people tended to view others’ content through the lens of their own self-concepts as curated through algorithmic personalization.

Perhaps the most consistent perception mentioned by participants was the relatability of content creators on TikTok, regardless of what category of video they made. One participant (P3) mentioned that they were seeing people “very similar” to them, while another (P12) found that she enjoyed

442 “watching stuff that [she could] relate to about parenting” because of the parts of participants’
 443 self-concepts that overlapped with content creators. Other participants remembered thinking “oh
 444 my god, I’m not the only one who feels this way!” (P23) after seeing content about a TV show they
 445 enjoyed or that they were “not alone” (P24).

446 In contrast with other platforms that have algorithmic recommendation systems that primarily
 447 rely on content from members of one’s network of known ties, it was not considered particularly
 448 important for participants on TikTok to have many overlapping interests with a singular other user
 449 on the platform. For example, one participant (P18) who enjoys musical theater and singing noted
 450 the following about Kristen Chenoweth, an actress and singer:

451 *“She posted another video where she was harmonizing with the fire alarm... I’ve had*
 452 *similar things where... I’m like, ‘Oh... the vibration from my toothbrush makes this*
 453 *sound... and then lets me harmonize to it.’ And so it’s totally relatable.”*

454 Where does this feeling of relatability stem from, even among participants and content creators who
 455 have minimal interests or identities in common? In the case of our participants, relatability appears
 456 to be driven by the familiarity of another’s self-concept when compared to one’s own, even if these
 457 self-concept dimensions are only partially overlapping. Further, relatability is largely experienced
 458 in a content-based, rather than person-based manner, similar to the phenomena noted by Zulli and
 459 Zulli [77], as well as Abidin [1] and Klug et al. [42]. One participant (P6) even mentioned that people
 460 were just “vessel[s]” for relevant content that could have “anybody’s face” on it, exemplifying the
 461 relative lack of importance of personal relationships as opposed to personalized content.

462 To further explain this phenomenon, we draw on Walton et al.’s [74] proposition of mere belong-
 463 ing, or the “minimal, even chance, trivial, or potential, social connection with unfamiliar others.” In
 464 past psychological research, feelings of mere belonging have led to increased interpersonal liking
 465 or better outcomes in social interactions, even in transitory or short-term settings. However, many
 466 of our participants had minimal direct social interaction with content creators or other users of the
 467 platform, although exposure to videos remained transitory. Some participants were even able to
 468 pinpoint the source of mere belonging, with one participant (P7) stating that “you don’t talk to
 469 [people on the sides]... you don’t know them, but you feel that sense of connectedness because you
 470 both... like one thing.” A noteworthy instance of this was described by another participant (P23):

471 *“I am Mexican, but it was very hard for me to learn Spanish. And so TikTok made this*
 472 *whole thing - they call them the ‘no sabo’ kids. [It] means ‘they don’t know’ Spanish. So*
 473 *I was on ‘no sabo’ kids for a long time and they just don’t know Spanish [either]. And*
 474 *it was cool to see how many people who are so into their culture and love everything*
 475 *about being Mexican - but just don’t know how to speak Spanish - come together. It*
 476 *was really nice actually.”*

477 In the case of this participant, no sabo kids are people who share a specific life experience with
 478 her, which in turn brings about positive feelings towards them, but who she otherwise does not
 479 directly interact with. Other participants noted similar feelings of ephemeral belonging to the sides
 480 of TikTok that they were also on. One participant (P2) mentioned that she “never post[s] videos”
 481 and she “very rarely comment[s]” but does feel that other TikTok users “share similar sentiments
 482 as [her].” For these participants, algorithmically personalized content allows them to see others
 483 who share similar aspects of their self-concept and reap some social benefits, such as feelings of
 484 connection, without direct interpersonal interaction.

485 Seeing others’ content through the perspective of parts of one’s self-concept, as well as the
 486 effect of mere belonging, can be further accentuated by the presumed number of people on a side.
 487 Participants described the benefits of sides with fewer other viewers, such as feeling more unique.
 488 One participant (P16) noted that “most of the time...I see [the videos] before [they] blow up.”
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491 Similarly, another participant (P6) noted that “once you get deep enough into the TikTok [sides],
492 you get a lot of videos that don’t have that many views so you feel like you’re... really important.”
493 Further, P9, who creates content, mentioned that they prefer “a smaller audience... so I can actually
494 see... how [people are] relating to the video.”

495 Although there is no way for participants to truly know how many people are on the same side
496 they are on, they can calculate estimates using the metrics that TikTok makes visible, such as the
497 number of views, likes or comments. Overall, participants intuit that greater degrees of algorithmic
498 personalization, experienced through hyper-specific content made by others, means that aspect of
499 their self-concept is potentially more unique.

501 4 DISCUSSION

502 This research explores how algorithmic personalization processes inform user understandings of
503 identity and shape their orientation to others. We focus on the platform TikTok, widely recognized
504 colloquially for the responsiveness of its content recommendation engine [61, 63], and explore
505 how TikTok users perceived the FYP algorithm in relation to their self-concept. Our participants’
506 experiences with the FYP algorithm reflected a recognition of parts of their identity in the content
507 recommendations and a subsequent desire to bring algorithmic representations of themselves into
508 alignment with their own self-concept. Our participants generally understood this alignment to
509 be a cyclical interaction of co-production between the algorithm itself and their own actions [38],
510 whereby the algorithm was appraised in terms of its ability to reflect the multifaceted and dynamic
511 interests of the user. At the same time, our participants felt that their behaviors could shape the
512 algorithm’s ability to accurately reflect their interests and preferences. Shaping of the algorithm
513 happened in two distinct ways: through participants’ organic interactions with platform content
514 and through their strategic attempts to influence the algorithmically-curated content.

515 Despite tending to just watch content on the platform rather than creating content or engaging
516 directly with other users, multiple participants reported positive feelings toward other people who
517 had similar interests or identities - even though little to no interaction took place. Other people
518 shown to them on the platform were seen as highly “relatable,” because they were understood
519 to be similar to the user in some way deemed relevant by the algorithm. As such, the algorithm
520 facilitated feelings of “mere belonging” towards others on the same side as participants.

521 We synthesize and extend these findings below by introducing an analytic framework that
522 coalesces our findings and can help guide future work, drawing from literature on algorithmic
523 interactions and self-concept. This framework contributes a new approach to understanding how
524 people understand and experience personalized algorithms.

525 4.1 The Algorithmic Crystal Framework

526 Building on insights from our qualitative data, as well as previous scholarship on the “crystallized
527 self” [70, 71], how people perceive personalized algorithms [19, 25, 28], and relationships between
528 the TikTok algorithm and identity (e.g., [6, 38, 41, 59]), we propose a novel conceptual model to
529 understand how people think about and interact with personalized algorithmic systems. Drawing
530 on the metaphor of crystals and their properties, the *algorithmic crystal framework* is an analytic
531 frame that captures user understandings of how personalized algorithms (1) interact with user
532 identity by *reflecting* user self-concepts that are both *multifaceted* and *dynamic* and (2) shape
533 perspectives on others encountered through the algorithm, by orienting users to recognize parts
534 of themselves *refracted* in other users and to experience ephemeral, *diffracted* connections with
535 groups of similar others. We discuss each of these properties in detail below.

540 4.1.1 *Reflective*. Crystals have several properties that we draw on for our framework. Crystals
541 are solid structures consisting of flat facets which can be shaped over time into multidimensional
542 prisms that capture and transform light. One transformation is reflection, or returning light back
543 to its source. In the algorithmic crystal framework, algorithms are understood to be *reflective* of
544 various dimensions of the self, including one’s interests and identities. This echoes French’s [28]
545 notion of the algorithmic mirror, in which algorithmic systems “mine one’s online activity, infer
546 one’s traits, and reflect those traits back to a person in the form of personalization.” Similarly, Hess
547 [34] also argues that interactions with digital technology are often “more like looking into a mirror
548 than looking out a window” in that we see more parts of ourselves than we see of others. Further,
549 Seaver [54] describes how successful recommender systems have to work in conjunction with
550 users’ psychological orientations in order to be truly captivating. In our data, reflection took the
551 form of the FYP algorithm curating content for participants that they felt represented their interests
552 or identity, supporting similar findings in other research on TikTok [4, 37, 57]. That is, people felt
553 that parts of their self-concept were accurately *reflected* back to them in the content provided by
554 the algorithm.

555 4.1.2 *Multifaceted*. The algorithmic crystal framework reminds us that algorithmic reflections of
556 the self can be *multifaceted* (see Figure 1) as well, as opposed to being flat, one-dimensional, or
557 oversimplified. Similar to work on the crystallized self, which draws on the imagery of the crystal
558 as prismatic to characterize the self as fundamentally multidimensional [70, 71], we found that our
559 participants valued when the algorithm was able to reflect their self-concepts as a constellation of
560 identity facets. These ranged from core traits like ethnicity and sexual orientation and deeply-held
561 passions, to fleeting interests and new discoveries.

562 Previous work, particularly on TikTok, has found that people understand personalization pro-
563 cesses as placing people into different categories and showing content that is thought to fall within
564 these categories [57]. Indeed, one complaint that participants often have of personalized recommen-
565 dations is that “maybe someone isn’t defined by a [single] category” [26]. Karizat et al. [38] also
566 notes the potential expansiveness of one’s self-concept in a related way, discussing the reflections
567 of both person and social identities. A crystal can be held up to the light and rotated to reveal one
568 facet at a time; likewise, our participants were shown one piece of content at a time on their FYP
569 and were able to recognize the various facets, or “sides,” that pieces of content belonged to. The
570 metaphor of the algorithmic crystal, then, highlights how algorithmic representations can capture
571 and reflect users’ many identity components but also, when rotated, allow users to discover new
572 ones. Just as elements of identity can range from the general to the niche, facets can come in a
573 variety of sizes.

574 4.1.3 *Dynamic*. The algorithmic crystal framework also highlights how the self is *dynamic* and
575 changes over time. Though the hard structure of crystals may evoke images of rigidity, prior work
576 on the crystallized self highlights that they can take on an infinite variety of shapes, that they can
577 “grow, change, alter, but not [be] amorphous” (Richardson in [71]); with the algorithmic crystal,
578 this fluidity is reflected back to the user via content recommendations that similarly adapt and
579 shift over time (see Figure 1). Just as users may grow in new directions and explore new interests,
580 the algorithmic crystal is assumed to be continuously changing: creating, removing, and refining
581 new facets to represent the user over time. The dynamic nature of the algorithmic crystal also
582 emphasizes the role of the user in shaping the form of their algorithmic representations, a process
583 that Karizat et al. [38] discuss as a form of co-production: wherein individuals shape the algorithm’s
584 recommendations and the algorithm in turn shapes how they understand themselves.

585 Other research on TikTok has highlighted the algorithm’s dynamic nature as well; Simpson
586 and Semaan [59] claim that “engaging with content by liking it... was mentioned by all of [their]
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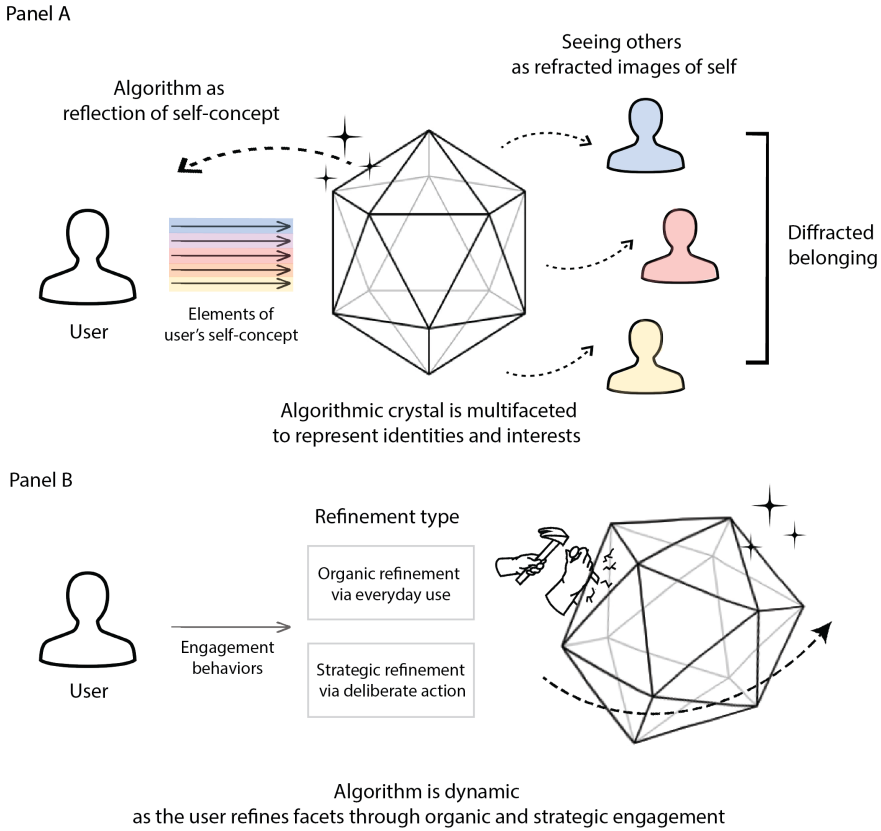


Fig. 1. A visual representation of the algorithmic crystal framework in two panels. Panel A emphasizes the reflective and multifaceted nature of the crystal, as well as the ability to see refracted images of the self and feel diffracted belonging. Panel B emphasizes the dynamic nature of the crystal and types of refinement.

participants as a way to influence the FYP algorithm over time,” with other scholars noticing similar patterns of behavior [38, 57]. Just as crystals can be processed to better reveal or occlude underlying patterns - cleaved, polished, even bruised - the algorithmic crystal can be transformed by the user to better reflect their own sense of self, whereby their algorithmic self and self-concept are aligned. We understand this alignment to be desired by users, for both pragmatic (i.e., better content recommendations) and psychological reasons. For instance, people often experience positive feelings about the self derived from seeing two versions of oneself in harmony, rather than dissonance [14, 36]. Further, recent empirical work has indicated that people may feel like certain technologies are extensions of the self [17, 48, 51]. Indeed, Ross and Bayer [51] note that technologies may be perceived as “a part of the self or... a reflection of the self.”

4.1.4 Refinement Strategies. People can dynamically refine the facets of the algorithmic crystal presented to them by engaging with the platform and providing more information about their preferences and tastes; this can occur organically or strategically. *Organic* refinement happens naturally, when users interact with content without the conscious goal of training the algorithm. Watching a particularly engaging clip two or three times, or saving it to show a friend later, would

638 fall into this category. Siles González and Meléndez Moran [57] conceptualized similar interactions
 639 between users and the TikTok FYP algorithm as a “depuration” process, in which “impurities” are
 640 removed from their feeds.

641 In contrast, *strategic* refinement, or polishing, describes deliberate and effortful attempts to train
 642 the algorithm with the goal of eliciting content that is more aligned with one’s current or desired
 643 self-concept (see Figure 1). People may vary in the extent to which they feel that the algorithm is
 644 reflective of who they truly are. However, they may also employ a variety of strategies to try to
 645 bring the algorithm’s recommendations into line with who they are, or want to be. Participant P18,
 646 who consciously sought out non-White content creators, engaged in a form of strategic algorithmic
 647 refinement. This refinement can be understood as a form of labor, where certain individuals exert
 648 time and energy to make the algorithm their own [38, 58]. There may also be elements of someone’s
 649 self-concept that they do not want an algorithm to recognize, such as an identity they are still
 650 exploring or an interest they are hoping to move away from. As a result, they may employ refinement
 651 strategies to shape the algorithm such that it reflects the person they would like to be.

652 As work on algorithmic domestication suggests [58], however, individuals may vary in the
 653 perceived amount of control they have over the algorithm and its representation of the self. For
 654 instance, not all users conceptualize algorithms as entities to be strategically polished or have, as
 655 described by Devito [19], high folk theorization complexity levels that support them in shaping
 656 the algorithm. However, refinement offers an important pathway to conceptualizing individual
 657 agency in the context of algorithmic systems [39]. Users can exert influence over what they see
 658 and how the algorithm sees them by purposefully avoiding clicking on content they do not want to
 659 see more of [22] or by purposely engaging with creators of marginalized backgrounds [38], like in
 660 the case of P18 in our dataset. It is important to note that organic and strategic polishing may look
 661 the same, because they involve the same behaviors, but motivations for the behaviors are quite
 662 different. Distinguishing between these two forms of refinement allows us to acknowledge the role
 663 of individual intentions in refining algorithmic representations of the self.

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 665 *4.1.5 Refractive.* Crystals can also bend the direction of light through refraction. Similar to reflec-
 666 tion, the process of *refraction* highlights perceived or presumed similarities between the self and
 667 other users, such as content creators. Viewing the algorithm’s recommendations as a reflection of
 668 who they are and what they like, people can come to see others that they encounter through the
 669 algorithm as *refracted images* of themselves: an egocentric orientation where people recognize at
 670 least one salient component of their own self-concept in others. In the case of our participants and
 671 the FYP algorithm, this might mean they recognize a sense of humor, a love of mystery books, or a
 672 shared ethnic or professional identity. As explored in other work on the experiences of LGBTQ+
 673 users, finding facets of one’s identity represented in algorithmically-shaped spaces like the LGBTQ+
 674 sides of TikTok can help people feel seen and affirmed in that aspect of their identity [59].

675 In Tracy and Trethewey [71], Richardson also notes that “crystals are prisms that *reflect* exter-
 676 nalities and *refract* within themselves” [emphasis added]. In the same way that external images
 677 viewed through a crystal are often warped by the contours of its internal structure, seeing another
 678 person through the algorithmic crystal can produce an altered view that emphasizes shared facets of
 679 interests and identity. Indeed, people can understand the algorithmized self as engaging reflexively
 680 with previous representations of themselves [6]. As a result, other users encountered through
 681 personalized algorithmic content may feel particularly relatable even in the absence of traditional
 682 markers of interpersonal communication and relationship development, such as message exchanges,
 683 because they feel like a refraction of the self. The salience of visual content and lack of direct,
 684 interpersonal interactions on TikTok, as well as folk theorization about how algorithms organize
 685 content around interest facets shared by many people, likely contribute to this process of refraction.

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687 4.1.6 *Diffraction*. Lastly, crystals can split beams of white light into a spectrum of colors through
688 diffraction. The algorithmic crystal can also *diffract* individuals' self-concepts into its constituent
689 parts in much the same way as a prism breaks up a singular beam of light into a spectrum of
690 colors. Unlike algorithms that attempt to find another individual that shares most aspects of a
691 user's self-concept, such as those on matchmaking platforms, the FYP algorithm exposes the user to
692 multiple groups of others who are each similar to the user in at least one specific way. For instance,
693 a user might view content from creators who enjoy baking, other creators who read fantasy books,
694 and still other creators who share the same political views. Each group of content creators is
695 similar to the user in at least one way, for as many facets as they have in their self-concept - a
696 concept we discuss as *diffracted belonging* (see Figure 1). The algorithmic crystal not only reflects
697 multifaceted aspects of one's self-concept back to the user (e.g., a love for baking), but also creates
698 ephemeral connections and facilitates mere belonging to groups of similar others if they share at
699 least one aspect of the self-concept with the user (e.g., other people who love baking), even if they
700 have nothing else in common. Wellman et al. [75] discuss a similar phenomenon of networked
701 individualism where "an individual's overall community will be heterogeneous because people
702 have multiple interests." In the case of our data, however, these connections are not interpersonal
703 relationships; previous work on imitation publics suggests that sociality on social media platforms
704 such as TikTok can be organized around the "shared ritual of content imitation and replication" with
705 strangers, instead of direct interactions with networks of known ties [77]. Similarly, the refractive
706 and diffractive nature of the algorithmic crystal organizes sociality around shared elements of
707 identity, allowing users to surface content from others like them without needing to truly interact
708 with them.

709 4.2 Applications and Extensions of the Framework

711 The algorithmic crystal framework serves as an analytic toolkit that provides a grammar for
712 examining how people understand and experience personalized algorithms and a generative
713 framework for future work. Building from an integration of our findings and prior work on
714 algorithms and identity, the framework contributes to the literature by allowing researchers to
715 rethink relevant theories and concepts regarding how people perceive and interact with algorithmic
716 systems. Below, we propose several pathways by which the algorithmic crystal framework can be
717 used to extend theory and inform new lines of research around the implications of algorithms in
718 self-concept development and social life.

719 First, future work could expand on these ideas by making fine-grained predictions about how
720 people's folk theories of algorithms relate to their behavior. Our data suggests an association
721 between users viewing the algorithm as reflective of their multifaceted and dynamic self-concept,
722 and their enjoyment of the platform. The degree to which algorithms are holistically perceived as
723 crystal-like may thus be related to decisions around continuance of platform use [19]. The individual
724 dimensions of the algorithmic crystal framework can be examined more closely to hone in on
725 how specific perceptions of algorithms (e.g., as more or less multifaceted or dynamic) shape key
726 processes and outcomes, including self-presentation and algorithmic literacy [2, 4, 20]. Future work
727 could also develop ways to assess perceptions of algorithms as crystal-like (e.g., "To what extent
728 does this algorithm reflect your identities and interests as multidimensional?"). Such measurements
729 introduce an opportunity to study between-person differences in perceptions of the same algorithm,
730 between-algorithm differences in user outcomes, and the impact of within-algorithm changes over
731 time - potentially in the context of user adaptation and resistance to algorithmic change (e.g.,
732 platform spirit [19]).

733 The algorithmic crystal can also serve as a useful framework for exploring the ramifications of
734 simplistic algorithmic representations of user identities or those that cannot adapt to an evolving
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736 sense of self. Given the findings of prior work on identity shift and algorithmic mirrors [28],
737 which demonstrate that algorithmically mediated self-presentations can change how people see
738 themselves, the implications of such stereotypical or outdated reflections of the self should be further
739 explored. While misalignment between the actual and algorithmic self may produce dissonance in
740 any individual, reductive reflections of the self (e.g., only being “seen” through one identity, such
741 as gender or race [76]) and outdated reflections of the self (e.g., being “seen” as a role that one may
742 no longer have) may be particularly harmful for certain communities. The failure of an algorithm
743 to capture the self in full as it changes over time may be particularly detrimental for individuals
744 from marginalized identities, for whom self-presentation is of heightened importance [19], and
745 individuals who are undergoing or have experienced a major life change (e.g., adolescents, veterans,
746 widows or divorcees [31]).

747 On the other hand, the multifaceted and dynamic nature of the crystal may facilitate explorations
748 of how experiences with algorithms may have self-transformative effects. Identity shift refers
749 to the process of self-transformation resulting from intentional self-presentation in a mediated
750 context [10]. While prior research has examined how algorithmic feedback can lead to identity
751 shift by intensifying particular attributes (e.g., introversion, extraversion [49]), the dimensions of
752 the algorithmic crystal may serve as a guide for extant research on more diverse forms of identity
753 shift. For instance, people may experience tension between the algorithmic representation of their
754 true self as produced by organic interactions with the algorithm, and the aspirational version of
755 themselves they may seek to cultivate through strategic refinement. In addition to highlighting
756 distinctions between real and desired selves, engaging reflexively with digital representations of
757 the self has been shown to prompt self-exploration [16] and influence behavior [33]. For instance,
758 students who interacted with altered digital representations of themselves as senior citizens became
759 more conscious of their financial futures and were thus motivated to save more for retirement
760 [60]. What might be the implications of interacting with a multifaceted, dynamic algorithmic
761 representation of the self that can be co-produced and shaped by the user? Applying the framework
762 could allow for nuanced research regarding how personalized content recommendations change
763 people’s understanding of who they really are.

764 Beyond individual identities, Tracy and Trethewey [71] argue that “by conceiving of identities as
765 ongoing, emergent, and not entirely predictable crystals, people are forced to acknowledge a range
766 of possible selves embodied in a range of contexts - even as they are constrained by discourses of
767 power.” Similarly, the structural forces embedded in algorithmic systems can also be understood
768 through the lens of the crystal framework. Applying this lens, the algorithmic crystal provides
769 another mechanism that explains why algorithms may overrepresent certain identity facets, while
770 suppressing others. Users may vary in their awareness and perception of this difference, as examined
771 in Karizat et al.’s [38] work on algorithmic representational harms, or the “users experience[s]... of
772 being rendered invisible, trivialized, suppressed, or otherwise further marginalized on the basis of
773 their identities and the algorithm’s understanding of their identities.” As such, framing the internal
774 algorithmic logics that shape which identities and interests are amplified or minimized through
775 the framework of the crystal could support extant research on biases and harms. For instance, the
776 identity facets that the algorithm presents as the “default” when users first join a platform can
777 reproduce structural norms. In the case of TikTok, the unrefined algorithm promotes content from
778 white, straight, and conventionally attractive youth from the outset, reinforcing the notion that
779 these identities constitute the norm while othering individuals from marginalized identities [38].
780 Although people can strategically refine the algorithm over time, the burden of engaging in the
781 labor of refinement again disproportionately falls on individuals from marginalized identities.

782 The algorithmic crystal also contributes a new orientation to understanding social perceptions in
783 algorithmically-structured spaces. Our framework suggests that because personalized algorithms
784

785 are organized around an individual's self-concept, some users can come to view others they
786 encounter through the algorithm as refracted images of themselves: an orientation that assumes
787 similarities with visible others based on the folk theory that the algorithm is showing them content
788 reflective of some aspect of their self-concepts. This contributes to our understanding of how people
789 experience different kinds of sociality in algorithmically-curated spaces with specific affordances
790 [2, 6, 77], and demonstrates how folk theorization can shape social experiences. Additional work
791 that characterizes the affect and affiliation dynamics of this orientation to others could contribute
792 meaningfully to our understanding of self-concepts. Further, the framework could be applied to
793 understand how social relationships unfold on platforms affording algorithmic personalization and
794 visually salient content.

795 The crystal is particularly informative in illustrating the concept of what we call diffracted
796 belonging, a type of algorithmically-mediated connection that facilitates a sense of mere belonging
797 by connecting individuals to n networks of content for n identity facets represented. In the case of
798 TikTok, for example, diffracted belonging appears to be a function of user perceptions that they
799 are iteratively moving from "side to side" and traversing different groups centered around their
800 interests and identities. Diffracted belonging can be understood as a form of social translucence
801 [23], as it provides individuals with partial insight into the ways in which they are connected to
802 other communities of users. In this way, diffracted belonging can be seen as a counterpoint to
803 conceptualizations of algorithmic filter bubbles as stationary, unidimensional echo chambers [13, 47]
804 and a novel extension to psychological theory on mere belonging effects [66]. However, additional
805 work is needed to understand whether such diffractive experiences may recreate dynamics of
806 societal exclusion seen in interpersonal interactions, such as in-group and out-group exclusion
807 [35].

808 The image of the crystal as being polished or refined by the user connotes agency in one's
809 relationship with the algorithm, and could inspire new design choices. For instance, algorithmically-
810 curated social media content is often described in metaphorical terms like a one-dimensional
811 "stream," where the platform is the active subject that moves while the user stands still. Conversely,
812 consider an image of a person holding a multidimensional crystal that is polished to more accurately
813 reflect the aspects of their self-concept that they want to see, or even rotated to explore new
814 reflections if desired. Rather than positioning users as passive recipients of a feed, the dual processes
815 of algorithmic refinement build upon prior work on strategic curation with algorithms [22, 57]
816 to articulate how individuals can have agency in shaping their algorithmic selves. Further, there
817 are minimal feedback mechanisms for users to reduce unwanted content on their feed, and such
818 mechanisms are typically weak. How might users be able to remove whole networks of content
819 from something like the FYP?

820 The boundary conditions of the algorithmic crystal framework are likely to be jointly determined
821 through the interaction of both platform affordances and user experience. Indeed, prior work
822 on adaptive folk theorization indicates that human-algorithm engagement is often shaped by
823 structural features, including the technical features (e.g., content modality) of the platform and
824 the psychological characteristics of the user (e.g., algorithmic literacy) [19, 43]. More granular
825 examinations of how networks are organized on particular platforms may prove particularly
826 instructive. Some platforms, for instance, prioritize recommending any content relevant to the
827 user (e.g., TikTok, YouTube), while others prioritize content from known social ties (e.g., Facebook,
828 Instagram). Platforms that more easily afford content-based interactions [42] may better lend
829 themselves to analysis through the algorithmic crystal framework because of the emphasis on
830 personalized content tailored to users' identities. Comparatively, person-based interactions highlight
831 relationships between users and others on the platform and are thus less egocentric. Content
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833

834 recommendations in these cases may thus be more likely to be understood as derived from shared
835 ties, rather than reflections of the self.

836 Researchers might also apply the framework by investigating the length and modality of content
837 recommended by the algorithm. For example, an algorithm that hosts shorter videos like TikTok
838 may be more likely to be experienced as multifaceted, because of its ability to reflect a greater
839 number of interest facets in the same length of time. Further, algorithms that prioritize video or
840 image data may be more likely to facilitate feelings of refraction and diffraction because the content
841 provides additional visual and audio cues through which users can view others. Zulli and Zulli [77]
842 describe this through the concept of imitation publics, where videos allow for “physical imitation
843 (copying dance moves), reactive imitation (capitalizing and expanding on someone else’s video)
844 and narrative imitation (describing the same type of experiences).”

845 In terms of user experience, we anticipate that people who have more degrees of algorithmic
846 literacy or algorithmic awareness [19] may be more likely to view algorithms as crystal-like, due to
847 their understanding of how the systems learn from personal engagement to recommend content.
848 Similarly, an individuals’ conceptualization of platform spirit, or the underlying motivations of a
849 platform’s construction [19], may also be an important factor. A person who views algorithms as
850 exploiting users for monetary gain or manipulating attention may not believe the algorithmically-
851 curated content is an accurate reflection of themselves.

852 Finally, future work should investigate the contexts in which the algorithmic crystal may “break,”
853 or when the framework may not apply. The perception of structural changes in the platform,
854 algorithm, or the companies that produce them may fundamentally shift how individuals understand
855 the algorithm in relation to their self-concept [19]. As prior work on adaptive folk theorization
856 demonstrates, such a shift can be caused by a real-world change (e.g., TikTok updating its content
857 recommendation algorithm) or by a perceived change that is assumed to relate to the algorithm (e.g.,
858 a user feeling that the algorithm no longer responds dynamically to their interests). For instance,
859 a change to the TikTok algorithm in late 2021 that prioritized videos with high view-counts caused
860 thousands of users to perceive their algorithm as “broken,” after seeing content that they perceived
861 to be more mainstream than their usual fare [30]. On the other hand, users can also perceive their
862 algorithms as “broken” if they feel its recommendations are no longer in alignment with their sense
863 of self. This raises important questions, such as: How much change can an individual accommodate
864 before they no longer experience the algorithm as reflective? Indeed, future work should explore
865 the extent to which crystal-like experiences are temporally-bound, as the product of perceived
866 alignment between two constantly evolving entities: the algorithm and the user.

867 4.3 Limitations

868 Limitations of this work include the fact that we only interviewed participants who were students
869 at one of three universities in the Bay Area of California participating in research for course credit.
870 Seeing as location is a factor that influences the content people see on their FYP [69], understanding
871 how participants experience TikTok in various geographic regions, particularly outside the United
872 States, is an important area for future work. We also believe that understanding perceptions of
873 those with marginalized identities, especially those not adequately represented in our sample of
874 participants (e.g., LGBTQ+ participants), will shed additional light on how the algorithmic crystal
875 framework can be applied to issues such as algorithmic representational harms [38].

876 Further, even though we did not impose any prerequisites regarding how a participant used
877 TikTok - only that they had to be “active” users, our sample included only a few participants who
878 created content as opposed to consuming it. It may be the case that content creators have different
879 perceptions regarding how the algorithm is related to their self-concept, as they are often engaging
880 in acts of self-presentation for an audience [12, 20]. Especially in regard to processes of identity
881

883 shift, users interacting with the algorithm through content creation may receive more sources of
 884 feedback (e.g., comments or likes on videos) than those who primarily consume content, potentially
 885 accentuating self-perception effects.

887 4.4 Conclusion

888 We investigated TikTok users' perceptions of the platform, with an emphasis on how people
 889 thought about the algorithm in relation to their own self-concept. Through analyzing data from
 890 our 24 semi-structured interviews, we propose the *algorithmic crystal framework*. We found that
 891 participants generally believed that they were multifaceted and dynamic individuals with interests
 892 and identities that were expansive and changed over time. Participants typically felt positively
 893 toward the FYP algorithm because the personalized content accurately represented these varied,
 894 fluid interests and identities. Further, they believed that their interactions with the platform were
 895 influential in aligning their algorithmic selves, or the types of content they saw, with their actual
 896 selves. In general, participants also felt a sense of connection towards other users encountered
 897 through the algorithm because they were able to recognize parts of themselves refracted in other
 898 users and experience ephemeral, diffracted connections with groups of similar others. Lastly, we
 899 discussed pathways in which the algorithmic crystal framework can extend theory and inform new
 900 lines of research around the implications of algorithms in social life.

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