Chapter 31
Making Personalization Feel More Personal:
A Four-Step Cycle for Advancing the User Experience of Personalized Recommenders and Adaptive Systems

Shailendra Rao
Stanford University, USA

Jeremy N. Bailenson
Stanford University, USA

Clifford Nass
Stanford University, USA

ABSTRACT

The gold standard for customer service is catering to each individual's unique needs. This means providing them undivided attention and helping them find what they want as well as what they will like, based on their prior history. An illustrative metaphor of the ideal interpersonal relationship between retailers and consumers is the "sincere handshake," welcoming a familiar face to a familiar place and saying goodbye until next time, best symbolizes an ideal interpersonal relationship between retailers and consumers. In this chapter the authors offer a four-step cycle of this personalization process, which abstracts the key elements of this handshake in order to make it possible in mass digital consumerism. This model offers an ideal framework for drawing out the key lessons learned from the two previous stages of media evolution, Micro and Mass, as well as from social science and Human Computer Interaction (HCI) to inform the design and further the understanding of the rich capabilities of the current age of Digital Consumerism.

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PERSONALIZATION CYCLE: ABSTRACTING THE KEY ELEMENTS FOR THE HANDSHAKE

The key aspects of the interaction between the customer and retailer that make it feel personalized can be abstracted and broken down into a four-step cycle: 1) Gather user information and needs, 2) Build user model and profile, 3) Match user with appropriate available content, and 4) Present personalized content (see Figure 1).

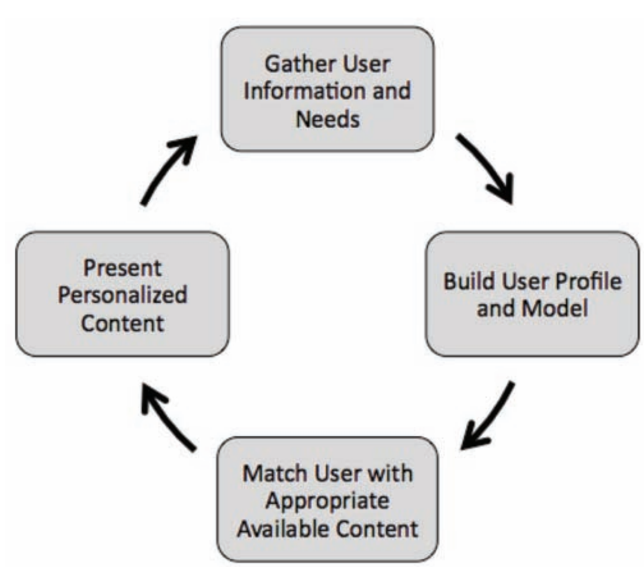
The first step in the interaction between media, content, product, or service providers and consumers with personalized service is assessing the consumer's demographics and unique preferences. Just as in retail, a key part of this initial assessment is trying to assess their goals- whether they are in search of something specific or browsing a la window-shopping. Once this has been done either through explicit or implicit input, the provider can formulate an internal model of whom the person is and what they might like. Then utilizing this model the provider can determine what available products or services will best suit this particular consumer. Finally, based on the previous three steps, the provider can assess how to best package and frame the recommended content when presenting it to the consumer and follow through accordingly. This personalization process can be conceptualized as a cyclical one as the recommender agent can iterate and continue to refine their understanding and modeling of a user, expand their library of matching content, and improve on how they frame the personalized content when presenting it to each individual consumer. With the cyclical nature and striving for constant improvement the retailer can adhere to the age old adage that the customer is always right.

Together this four step-cycle abstracts the key steps necessary for personalization away from the intricate human production and computing processes necessary for execution. By doing so this model provides a framework for identifying exactly where the insights and future investigations from social science and HCI can help make personalization feel more personal for consumers.

Micro Consumerism: A Friendly Handshake

A frequently visited local video rental store provided an ideal setting for this handshake to take

Figure 1. The personalization process



place. At this neighborhood store customers would be welcomed by a friendly greeting from a store clerk or owner, who would ask them how their previous movie recommendations turned out as well as suggest new ones based on the customer's feedback and prior likings. For the customer the purchase process was made infinitely easier and enjoyable because of this personalized service. From the seller's perspective the handshake was a key ingredient in building a better shopping experience and thus a stronger business, by helping project a caring image, increasing sales with targeted recommendations, and cultivating a regular loyal consumer base.

Personalization was a critical factor in making the customer-seller relationship feel truly personalized at this stage of consumerism precisely because of what it did at each aspect of the four-step personalization process. The manner by which the store clerk or owner gathered their customer's needs was important as the right questions were asked in the right manner for each individual. Because the retailer had developed a relationship with the customer and knew how to parse the information they gathered from them, they were able to properly build a profile and model of what each individual would like, which led to a natural matching with appropriate available content (Linden, Smith, & York, 2003). Finally, the store clerk or owner was able to present this personalized content in a targeted and transparent manner, which spoke to each individual at a personal level and made the recommendations and overall service feel more personal.

Mass Consumerism: The Efficient, But Impersonal Handshake

Unfortunately many aspects of this handshake were lost in recent times with the emergence of *mass media* (media designed for a very large audience) (DeFleur & Dennis, 1991; McQuail, 2005), *media consolidation* (the majority of major media outlets owned by a few corporations) (Compaine & Gomery, 2000), and the proliferation of big businesses to the detriment of local mom-and-pop shops such as the neighborhood video rental store, which fostered and were dependent on sincere interpersonal relationships with their clientele. In the name of profit and efficiency truly personalized service and media existed only at the margins of society with special interest venues.

To accrue the benefits of the handshake from Micro Consumerism at each of the four outlined levels of the personalization process which were so critical to the previous model of customer-seller relationship, media conglomerates drew on several strategies to blur the lines between *interpersonal* (Gemeinschaft) and *mass media* (Gesellschaft) (Beniger, 1987). These strategies centered around feigning the sincerity of the handshake commonly found at the previously ubiquitous local video rental store. Strategies for mass media productions to conceal audience size with the aim of generating pseudo-communities include simplicity, personal stories, personal agents, interactivity, emphasis on emotion, and production values. Media providers and retailers used these strategies with varying success however and the handshake frequently found at the neighborhood store was never fully attained in all arenas with the same level of sincerity.

It increasingly became the norm to visit a chain brick and mortar retailer such as Blockbuster (J Nielsen & Mack, 1994) or Hollywood Video (Izard, 1971) as opposed to going to the quickly disappearing neighborhood video rental store. Oftentimes gone with this transition were the familiar faces that were able to attend to each individual's needs because they knew them at a personal level. Instead of being greeted by a store clerk who knew their previous viewing history and could make personalized recommendations based on their prior likings, consumers found themselves unattended and unassisted in a do-it-yourself shopping experience. The burden was primarily on consumers to satisfy their own needs during this stage of media evolution. Critical elements represented in this handshake that made consumerism feel personalized in the previous stage were missing. Consequently the gold standard for customer service normally found in the previous stage of consumerism was lost.

Lost in this transition from Micro Consumerism to Mass Consumerism were the wins at each of the four levels of the personalization process, which were major factors in attaining that friendly handshake between retailers and consumers. Because there was less emphasis on individualized service and fewer opportunities, it was a seemingly impossible challenge to both gather a customer's individual needs and build an accurate profile and model of them fully considering their uniqueness, rather than making gross guesses about them based on their assumed demographic. The consumer also suffered from poorly trained sales people and store representatives who many times lacked a deep understanding of the products and services they were providing (Del Colliano, 2008). Consequently, matching them with appropriate available content and presenting this in a targeted and persuasive way were not strengths of this stage of consumerism.

It would be a mistake to only paint a gloomy picture here however, as this stage in media evolution brought many positives for both providers and consumers. For providers and merchants some of the benefits these changes brought included much more rapid production of higher quality media, larger audiences, and lower costs to production and distribution. Consumers also benefitted with quality standardization, lower prices, and easier access to these media goods.

Digital Consumerism: Reviving the Handshake with the Best of Both Worlds

Over the past decade there has been a seismic shift in these interactions between providers and consumers because of the very recent dramatic technological advances of the digital information age. This has allowed for the possibility of that gold standard of customer service to be reconstructed without losing the efficiency and other tangible benefits of Mass Consumerism. Instead of succumbing to the limitations and impersonal nature of a one-to-many broadcast model, content providers and advertisers can tailor their messages, services, and products to meet the specific needs of a particular individual with a very personalized feel. The symbolic handshake can be resurrected with the technological affordances of the present stage in media evolution.

Innovations in and high adoption rates of cable and digital television, the emergence of the Internet, and the prevalence of mobile phones have created a setting where content providers and advertisers can more effectively feign a personal one-to-one relationship with the members of their target audience through personalized media systems far more intelligently than with the first phase of Mass Consumerism. The technological advances that have set the stage for this shift are numerous and include, but are not limited to, the digitization of content, cheaper and increased storage capacities, advanced machine learning algorithms, faster data transmission speeds, and increasingly ubiquitous cell phone connectivity (Negroponte, 1995). Technology has played a major role in bolstering the efficiency and effectiveness of media suggestions (providers), requests (consumers), transmissions (providers), and reception (consumers).

Personalized recommendation engines best illustrate the extent of the power that this media shift offers. They enable media providers to revive many of those critical elements of the neighborhood corner store, namely being cognizant of each individual consumer's past history and what they might like. By having an understanding of who a consumer is, their tendencies, past attitudes and behaviors, as well as a model of what this means, producers of these recommendation engines can cultivate an intimate relationship with their customers. When done properly and optimally, personalized recommendation systems solve many of the problems that surfaced with the transition to Mass Consumerism. They can revive many of the positives from the more localized and interpersonal consumerism evident in the neighborhood video rental store, and offer new opportunities for advancing consumerism that were not possible in the previous phases.

It has become increasingly common in this present age of media consumerism to use online services to rent or purchase movies in place of the neighborhood video rental store or the massive brick and mortar video chain (Buckley, 2008; eMarketer, 2006, 2007; Reisinger, 2008). Some popular services are Netflix, iTunes Store, and Amazon (Branco, Firth, Encanacao, & Bonato, 2005; Hitwise, 2007; Netflix; *Sharing, Privacy and Trust in Our Networked World*, 2007; Ward, Marsden, Cahill, & Johnson, 2001). All of these services have an underlying recommendation engine, which serves two main functions 1) increase sales by quickly matching consumers with content they will like and 2) make their service feel more personalized for the end consumer by bringing back the aspects of the handshake that were sorely missed with the transition to mass media.

Currently consumers can go to one of these or other e-commerce venues and shop in an online personalized environment for a plethora of products, services, and media content. Across all of these shopping places they can communicate to the retailer what their specific movie interests are either through *explicit* means (self-reports about objective personal characteristics, self-assessments with respect to general dimensions, self-reports on specific evaluations, or responses to test items) or *nonexplicit* ones (naturally occurring actions, previously stored information, low-level indices of psychological states, or signals concerning the current surroundings) (Jameson, 2002). This interactivity between providers and consumers helps foster a relationship that can closely approximate the best aspects of the local neighborhood video rental store shopping experience. Specifically, these online video markets can welcome their customers just like those local shops did, by asking how their previous movie recommendations turned out as well as suggest new ones based on their feedback and past favorites.

Additionally, because of the power afforded by their online recommendation engines these retailers can make new connections with their customers with personalized one-to-one marketing messages via various mediums (email, text messages, other websites) and by allowing them to set up wish lists and notifications. By bringing back the key ingredients that made that handshake possible as well as exploring and experimenting with new opportunities, personalized recommendation systems enable media and content providers to offer customers an easier, more efficient, and more enjoyable purchase process than possible with the previous two stages of consumerism.

But it is important to note that simply having a recommendation engine is not an end all solution to offering a personalized experience, nor a guarantee that the handshake found in the neighborhood store will be revived. Similar to how mass media utilized the techniques outlined by Beniger (Beniger, 1987) to feign sincerity to overcome some of the key problems with Mass Consumerism in terms of providing the handshake, personalized online recommendation systems necessitate a framework based on an empirically grounded understanding of people's interactions to make them feel truly personalized. To take full advantage of the power that digital media affords in this era for empowering consumers with a personalized experience, media theorists, researchers, and producers need to focus on these interactions and experiences from a user centered design perspective.

Personalizing consumer experiences in this current stage of media production and consumption is not only a task for engineers and business experts to tackle and solve. It does not simply consist of issues for computer scientists to work on: improving user modeling, designing better adaptive algorithms to improve accuracy rates, or increasing data transmission speeds. Neither is it just for business strategists to worry about targeting specific markets, expanding inventory, or forming partnerships. A necessary component for the success of online recommendation services and more generally personalized and adaptive systems is a grounding in principles and findings from the interdisciplinary field of HCI and the social sciences.

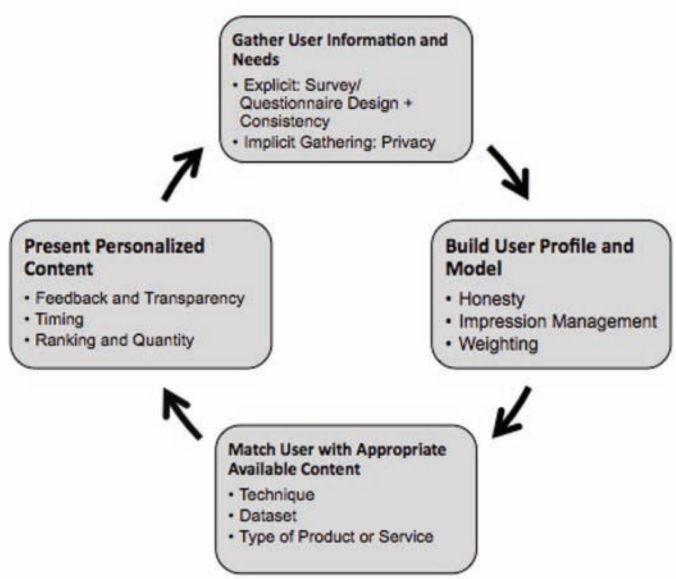
The four-step personalization process highlights each of the key areas where HCI and social science can advance Digital Consumerism, particularly recommendation systems, to its apex in terms of the relationship between providers and consumers (see Figure 2). Drawing from lessons learned in survey and questionnaire design and privacy can greatly improve how adaptive systems gather user information and needs either explicitly or implicitly. Building user profiles and models by adjusting appropriately for impression management and honesty can make a dramatic impact on the performance of these technologies. Matching users with appropriate available content is a technology problem, but the recommendation mechanisms chosen cannot be done in isolation from user needs. Lastly, understanding the prior work on and future directions for feedback, transparency, timing, and ordering can help ensure that the fruits of the three previous steps are effectively presented to the end consumer.

The cyclical nature of the personalization process afforded by the digital age, parallels repeat visits to the neighborhood corner video store. Much in the same way store clerks at the neighborhood video store cultivated a personal relationship with their loyal costumers, personalized recommendation systems develop this relationship through repeated usage. At its optimized case, the cyclical fashion of this process helps resurrect the handshake, the symbol of the gold standard for customer service.

Chapter Goals

The goals of the remainder of this chapter are two-fold and structured by the framework offered by the four-step cyclical personalization process outlined above: 1) explore and detail how designers of personalized systems can replicate the

Figure 2. Using this model to take digital consumerism to the apex



handshake from the local neighborhood corner store, overcome the limitations of the era of Mass Consumerism, and reap the many benefits from the technological advances of the current Digital stage of media evolution and 2) identify open questions and key opportunities in this space for media researchers and theorists to pursue to make personalization feel even more personal.

Gather User Information and Needs

At this stage of the personalization process the chief aim is to collect accurate information about the consumer and identify their individual needs. This phase can be likened to the first encounter between a customer and a store clerk at a video rental store. After the friendly greeting the store clerk's next critical task is to formulate an understanding of whom their customer is and how to best please them. In an ideal case the store clerk puts the customer at ease and encourages them to divulge as much as possible about their background, personality, and interests, which makes it infinitely easier to properly build a mental model of the individual in the next stage of the personalization process. There are two ways for personalization systems to gather information from and the needs of their users: 1) explicitly and 2) implicitly (Jameson, 2002). The following sections outline the respective advantages and disadvantages of both types of information gathering in the context of personalized systems and some specific ways to ensure the information gathering at this stage leads to a user experience that feels more personalized.

Explicit Gathering

Explicit in this case means to gather information about a user including their self-reports about objective personal characteristics (e.g., age, profession, or residence), self-assessments with respect to general dimensions (e.g., interest level, knowledge level, or importance level), self-reports on specific evaluations (e.g., thumbs-up or thumbs-down), and responses to test items (e.g., a standardized battery of questions) (Jameson, 2002). Key benefits to gathering user information explicitly are that it is a quick way to collect user information that is fixed or typically remains static, users know exactly what information about them is being stored and collected which escapes many privacy issues and concerns, and the physical barrier for inputting personal characteristics can be set very low on the web if the inputs are designed with a few radio buttons, check boxes, and dropdown menus. On the other hand, one drawbacks is users have to invest time up front to construct a profile before they can see if the personalization system's recommendations are worth the effort. Moreover, they may not understand the questions and possible answers, they may provide socially desirable answers instead of reflecting their true self, or they may simply look for the answer that requires the least amount of thought to finish the profile building process as fast as possible.

Survey and Questionnaire Design

Explicit information gathering for personalized systems can leverage the rich body of work and lessons learned from survey and questionnaire design to improve upon its validity and reliability. There is a vast array of survey design and research resources readily available. Ozok (2009) provides an overview of survey design and implementation in HCI (Ozok, 2009). Pasek and Krosnick (2010) utilize insights from psychology to optimize survey questionnaire design in political science, which supplies a relevant and applicable review for advancing this step in the personalization cycle towards improving the overall personalization process (Pasek & Krosnick, 2010). At a high level it is critical to be mindful of the three basic rules of survey and questionnaire design enumerated by Pasek and Krosnick. They should 1) be designed to be as easy as possible for the ideal survey respondent, 2) discourage looking for shortcuts and simply looking to satisfy the interviewer, and 3) avoid unnecessary confusion and misunderstandings by adhering to conversational conventions as much as possible. Offering an entire survey and questionnaire design guide for explicit data gathering in the personalization cycle is beyond the scope of this chapter, but there are a few keys to remember which will be outlined here.

Open-Ended Questions vs. Closed Questions

In the context of a personalized recommender it takes a great deal of natural language processing capabilities and places great demands on computing resources to offer open-ended questions and interpret user responses. Consequently, closed questions with a fixed set of answer choices are a natural fit for this context. However, it is important to be cognizant of the drawbacks of closed questions. Unlike open-ended questions, which can require a great deal of thought and effort on the part of the respondent (Oppenheim, 1966), it is easy to quickly flip through closed questions and satisfice. Additionally when numbers are involved in the answer options (e.g. 3 hours, 5 books read, etc.) the midpoint of the offered range implies the norm which sends an implicit message to people and can affect their self-report (Norbert. Schwarz, 1995).

Pasek and Krosnick offer a useful tool when designing closed questions for improving its needs finding ability (Pasek & Krosnick, 2010). Before employing a closed question, it is useful to pretest an open-ended version of it on the population of interest. This helps ensure that the answer choices offered encompass all of the alternatives a user might consider in response to the particular question being asked.

Rating Scales

There are several guidelines about how to make the rating scales for closed ended questions more intuitive for users. These in turn improve the quality of the coding and interpretation done by system designers, researchers, and the corresponding algorithms in play. For *bipolar* dimensions which have a meaningful or interpretable midpoint (e.g. dislike a great deal to like a great deal where the midpoint is neither like nor dislike), 7-point scales have shown to be more reliable (Green & Rao, 1970). Conversely, for *unipolar* dimensions (e.g. not at all important to extremely important where the middle category "somewhat important" does not necessarily imply the absence of importance) ratings have been found to be more reliable when 5-point scales are utilized (Lissitz & Green, 1975).

Despite increasing cognitive costs, adding verbal labels on all rating scales rather than just leaving them only numbered, makes it easier for respondents to interpret the intended meaning behind the answer choices. This increases the reliability and validity of the user's ratings (Jon A. Krosnick & Berent, 1993; Norbert Schwarz, Knauper, Hippler, Noelle-Neumann, & Clark, 1991). These verbal labels should have equally spaced meanings as well (Hofmans, et al., 2007; Norbert Schwarz, Grayson, & Knauper, 1998; Wallsten, Budescu, Rapoport, Zwick, & Forsyth, 1986).

Rating or Ranking

For personalized recommendation systems it is useful to gather user preferences along ordinal dimensions (e.g. 1-Dislike a great deal to 7-Like a great deal) and run corresponding statistical analyses to compare user attitudes across multiple items. In these situations even though they can be more time-consuming for users, ranking questions produce more reliable and valid output than ratings as they are the product of less satisficing (Alwin & Krosnick, 1985; Jon A Krosnick & Alwin, 1987; Miethe, 1985; Reynolds & Jolly, 1980). For example, in the context of a dessert recommendation system attempting to gather a user's fruit delectation, it is more fruitful to ask them to rank their favorites amongst mangoes, strawberries, blueberries, pineapples, etc., rather than inquiring about how much they like each individual fruit and then running the analyses across items.

Ordering Effects

Two ordering effects in particular are important for improving the design of personalized systems at this stage: 1) *response order effects* and 2) *question order effects*. To sidestep both primacy effects, the inclination to select options at the beginning of a list (Belson, 1966), and recency effects, the inclination to select options listed at the end (Kalton, Collins, & Brook, 1978), designers can randomize the order of the answer options presented and utilize *seemingly open-ended questions* (SOEQ) (Pasek & Krosnick, 2010). SOEQ's use a short pause to segment the question from the response choices, which encourages respondents to think through the question as if it were an open-ended one (Holbrook, Krosnick, Moore, & Tourangeau, 2007). For example, in the case of a movie recommendation system trying to gather user likes and dislikes, instead of asking "If you had to pick your favorite gangster movie, would you pick The Godfather I, Goodfellas, Scarface, or Donnie Brasco?" it is better to ask "If you had to pick your favorite gangster movie what would you pick? Would you pick The Godfather I, Goodfellas, Scarface, or Donnie Brasco?", which reduces response order effects.

Four concerns stemming from question order effects are 1) *subtraction*, 2) *perceptual contrast*, 3) *priming*, and 4) *length*. Subtraction results from two nested concepts presented next to each other and it appears the questions although related are intended to be evaluated separately (e.g. a question about Microsoft Internet Explorer followed by one about Microsoft software) (Schuman, Presser, & Ludwig, 1983). Perceptual contrast occurs when two successive questions present a contrast (e.g. attitudes amongst a technophile audience towards Mozilla Firefox may be positively influenced if they are immediately preceded by their assessment of Microsoft Internet Explorer) (Norbert Schwarz & Bless, 1992; Norbert Schwarz & Strack, 1991). Priming happens when earlier questions increase the salience of certain attitudes or beliefs (e.g. preceding questions about Microsoft with those about Windows Vista may increase the chances of a poorer overall evaluation of Microsoft) (Kalton, et al., 1978). In terms of length of survey it is better to ask questions that are of primary importance and utility to the recommendation algorithms in play earlier, rather than later to reduce the chances of satisficing (J. A. Krosnick, 1999). As Pasek and Krosnick note, there is no simple solution for alleviating question order effects other than being cognizant of these aforementioned biases, as oftentimes a particular ordering of a question set is needed for coherence (Pasek & Krosnick, 2010).

Gathering Consistent User Input

Another key consideration when collecting explicitly supplied input is ensuring that the user is providing consistent responses that are not disrupted by system performance or variables in flux such as time of day. Inconsistent user input, particularly those resulting from attempts to game the system, add a tremendous amount of unnecessary confusion for both the underlying recommendation engine's processes as well as for the user. To aid personalized systems in their quest to offer a tailored user experience for each individual it is imperative that the data gathered at this stage in the personalization cycle paints a congruent picture of the user.

The experiment conducted within the context of a fictional and controlled online dating recommender in Rao et. al (2009) (Rao, Hurlbutt, Nass, & JanakiRam, 2009) demonstrated how using a person's own photograph can keep their responses consistent and prevent them from gaming the system when presented with poor quality recommendations. It remains to be seen whether the stabilizing effect of personal photos will wear off over time or whether these results hold in other recommender contexts. However, displaying a person's own photo appears to be one tool designers can add to their arsenal to improve the data gathering stage. In addition to investigating the aforementioned open questions about personal photo, future research can assess whether this is a useful tool for gathering consistent user input through implicit means.

Implicit Gathering

Implicit inputs to formulate user profiles include *naturally occurring actions*, *previously stored information*, *sensing psychological states*, and *deriving information from a user's current surroundings* (Jameson, 2002). Some of the benefits of this style of information gathering about users are that they are not required to invest any cognitive or physical effort and time up front, profiling can be done unobtrusively in the background, and the problems about self-report noted above are avoided. Key concerns about this approach have to do with privacy and transparency. Users may not be comfortable or even realize that personal information and inferences about them are being collected and made. Another limitation is that systems using this method can require users to use the system for quite some time before it is able to collect enough information to make solid and valuable inferences about a person.

Privacy

As it is across the entire personalization process, privacy is a major concern for both users and recommendation system designers. Although this topic applies broadly to the entire personalization process, it is of particular concern for implicit user data gathering and represents the endpoint of the continuum for personalization systems privacy invasiveness (Cranor, 2004). Both Cranor (2004) and Teltzrpw and Kobsa (2004) (Teltzrow & Kobsa, 2004) provide a detailed overview of the many privacy risks, concerns, preferences, laws, and self-regulatory guidelines for personalized systems. The following briefly picks out some key ways to reduce user privacy concerns in this space.

Brodie et. al (2004) found that user willingness to share personal information in an e-commerce setting increased when they were allowed to view, edit, and delete their own data (Brodie, Karat, & Karat, 2004). They also suggested that privacy concerns can be sidestepped for personalized systems if users can specify to the system when it is useful for it to collect their data. Another design guideline offered was to let users manage and select from different identities when interacting with a website as they may be more willing to disclose personal information or be monitored under the guise of a pseudo name. The majority of internet users are concerned about being tracked ("Cyber Dialogue Survey Data Reveals Lost Revenue for Retailers Due to Widespread Consumer Privacy Concerns," 2001) and as Brodie and colleagues posit asking users for explicit consent may be one way to allay their fears. This ties into metaphors about dating and customer service. After the customer has been on a few "dates" with the marketer, it is easier for them to disclose more of their personal information (Godin, 1999).

All of these design guidelines revolve around giving users more control of the data gathering stage which ties into the finding that consumers react more positively to organizations when they have a higher perceived level of control (*A Survey of Consumer Privacy Attitudes and Behaviors*, 2000; Hine & Eve, 1998). Whether information about an individual is being collected through explicit or implicit means, it is critical to be respectful of their concerns and make them feel both in control and cognizant of exactly what is occurring at this stage in the personalization cycle.

Build User Profile and Model

Once the personalized system has gathered an individual user's preference, needs, and goals it is time to the build a model and formulate a profile of the user. This step in the personalization process is about interpreting and assembling all of the user information gathered in the previous phase. The neighborhood video rental store parallel is the clerk taking a few moments and reflecting upon what their customer has intentionally or unintentionally communicated to them as well. This pause helps the store clerk internalize everything they have just learned about their customer through proper listening, deduction, and inference right before seeking appropriate video title recommendations.

Similarly personalized systems at this stage of the personalization process need to correctly assemble the pieces of the puzzle to determine whom exactly the individual user is and what their unique needs are to ensure that it is offering an intelligently personalized experience. To achieve this, the underlying computing algorithms in play here should be driven by an understanding of *impression management*, *correction factors*, and *proper weighting* of the input the consumer has provided explicitly or implicitly in their interactions with the recommendation system.

Impression Management

Understanding people's impression management when interacting with these systems is a key step in ensuring that their entire experience feels personalized. It is critical to always keep in mind that data gathered about the user can be contaminated and corrupted by their own conscious and unconscious efforts to present themselves in a particular light. Failing to do so may lead the personalized system and its underlying algorithms astray and as a consequence, result in sub-optimal recommendations and overall user experience.

This can be likened to the research on *impression management*, *face-work*, and *presentation of self* in human-human interactions (Dillard, Browning, Sitkin, & Sutcliffe, 2000; Goffman, 1956, 1959; Schlenker, 1980; Tedeschi, 1984). The framework which Higgins (1987) uses to categorize the domains of the self is useful for designers of personalized systems to be cognizant of: the *actual self* (who one really is), the *ideal self* (who one would like to be), and the *ought self* (who one feels it is their duty to be) (Higgins, 1987). This trinity of self is applicable in this domain as it outlines the different motivations behind how users represent themselves to an interactive personalized system via explicit and implicit means. For example, a user may misrepresent themselves in a questionnaire that the system needs to learn about their goals and desires by intentionally presenting themselves as how they strive to be, rather than as how they actually are. Likewise when a user is being monitored or under the watch of a personalized system working to profile them, they might change their normal behavior to live up to a version of their self that they think they ought to be (Higgins, 1987). At this stage in the personalization cycle it is imperative to utilize this framework when interpreting the collected user data from the previous step.

It is worth noting that *computer mediated communication* (CMC) between people can have some advantages over human-human interaction with respect to people putting on a different face so to speak. This is illustrated in Bargh et al. (2002) where compared to face-to-face interactions, Internet interactions allowed individuals to better express aspects of their true selves to others (Bargh, McKenna, & Fitzsimons, 2002). In an online setting people felt more comfortable expressing aspects of themselves that they wanted to express in the real world but felt unable to. Furthermore, it may be easier for people to present their various negative aspects given the relative anonymity of online interactions. See Ellison 2006 for a literature review of self-presentation and self-disclosure in online contexts, specifically in CMC (Ellison, 2006). One natural direction for future research in this space is to explore how the various aspects of a user's context, namely time, physical location, and activity, affect their impression management with personalized systems trying to build an accurate and useful profile of them.

Honesty

Hancock et al's (2007) investigation of honesty in the online dating space offers an illustration of why it is critical for designers of interactive systems to not simply take user inputs at face value (Hancock, Toma, & Ellison, 2007). Their study of 40 males and 40 females showed that deception in dating profiles was common: 55.3% of males and 41.5% of females provided deceptive information about their height, 60.5% and 59.0% respectively did so for their weight, and 24.3% and 13.2% misrepresented their age.

More specifically this study offers some specific correction factors for each of these personal attributes. Both men and women overstated their height; on average men did so at .57 inches (SD = .81 inches) and women added on .03 inches (SD = .75 inches). This effect was more pronounced for short men and women. Similarly both men and women underreported their weight, but women did so more than men. On average women said they were 8.48 lbs lighter than they actually were (SD = 8.87 lbs), while men underreported their weight by 1.94 lbs (SD = 10.34). The average age deviation found was .44 years with a range from 3 years younger to 9 years older. No difference in age deception was found between men and women. By applying the results of this study as correction factors system designers in working on online dating matches can appropriately fix the user data that fuels their personalized algorithms, so that it provides a more valid view of the user being profiled.

For the purposes of designing personalized recommendation systems it is not necessarily important why people are misconstruing their actual self to and through digital media; what is important is correcting for it because using raw, uncorrected data to drive the personalization process will result in sub-optimal user experiences. The investigation in Hancock et. al (2007) offers a starting point for research specifically targeted at improving this stage of the personalization process (Hancock, et al., 2007). People's honesty and impression management in other product and service contexts remain unexplored and worthy of much research attention. The specific goal for this work is to determine whether the user data collected actually means what it is supposed to mean and if not, then how to adjust it accordingly. Considerations towards user honesty and their impression management are imperative for driving the personalization algorithms detailed in the next step in the personalization process.

Weighting

Another important consideration at this stage of the personalization process is determining how much value to assign to each of the explicitly and implicitly gathered inputs about an individual user. Rich's work on using stereotypes about a person, particularly their gender and race, to quickly build a small and deep model of them illuminates the potential benefits of properly weighting different traits of a person (Rich, 1979a, 1979b, 1983). This work made use of a system called Grundy, which used a limited set of stereotypes such as feminist, intellectual, sport-person, about a user to generate novel recommendations. Grundy had a much higher success rate of recommending novels that users liked when using these stereotypes about a person than compared to random suggestions. This illustrates how heavily weighting various aspects of an individual user can positively shape the personalized experience being offered.

In short to provide an intelligently personalized experience all of the collected aspects of an individual should not be given the same amount of weight. Research on how much emphasis to place on specific individual user traits during this stage is nowhere near being a closed book. This is not surprising given the diverse array of people and the products and services available for recommendation to them. Consequently concrete guidelines for system designers are not readily available for weighting traits. This leaves ample opportunity for future researchers. It may be the job of computer scientists to devise and adjust these weighting algorithms, but it is the responsibility of social scientists working in this space to explore and determine how much to weight various gathered aspects of an individual user to inform these computing processes.

MATCH USER WITH APPROPRIATE AVAILABLE CONTENT

For personalized recommendation systems this phase in the personalization process is a technology issue, dependent on the recommendation approach and algorithm chosen. On the surface it may seem that social science and HCI methodologies and design principles cannot contribute at this step in the personalization cycle for Digital Consumerism. However, that is not the case as the basis for generating recommendations cannot be disentangled from user perceptions concerning the quality and type of the personalized content, the systems' intelligence level, as well as the system's impact on an individual's cognitive and affective state. With this in mind we provide an overview of the various approaches to recommendation types that exist and are under development.

Techniques Used to Generate Recommendations

Personalized recommendation systems are often grouped into one of five methodologies: 1) *collaborative filtering*, 2) *content-based*, 3) *demographic*, 4) *utility-based* and 5) *knowledge-based* (Burke, 2002; Resnick & Varian, 1997; J. Ben Schafer, Konstan, & Riedl, 1999; Terveen & Hill, 2002). Collaborative filtering is a popular recommendation approach used on the web that filters and evaluates items based on the opinions of other people (J. B. Schafer, Frankowski, Herlocker, & Sen, 2007). Content-based recommendation systems rely on a description of an item and a profile of the user's interests (Michael J. Pazzani & Billsus, 2007). Demographic recommendation systems use personal attributes to categorize its users and make their recommendations according to associated demographic classes (Krulwich, 1997; M. Pazzani & Billsus, 1997; M.J. Pazzani, 1999; Rich, 1979a, 1979b, 1983). Utility-based recommendation systems are centered upon the utility function of each available recommended product or service for a user (Guttman, Moukas, & Maes, 1998). Knowledge-based recommender systems employ their functional knowledge of how an individual user's need is fulfilled by a particular item to provide recommendations (S. Brin & Page, 1998; J. Ben Schafer, et al., 1999; Schmitt & Bergmann, 1999; Towle & Quinn, 2000). Burke (2002) provides a detailed overview and analysis of these five popular recommendation techniques and their associated backgrounds, inputs, and processes (Burke, 2002).

Other adaptive techniques of note are *ability-based*, *learning personal assistants*, *critique-based*, *situational impairment adaption*, and *user interfaces that adapt to the current task* (Gajos & Jameson, 2009). Ability-based user interfaces adapt to the user's individual and actual abilities with respect to dexterity, strength, preferred input/output devices, visual acuity, color perception, etc. and respond accordingly (Gajos, 2007; Gajos & Weld, 2004; Gajos, Wobbrock, & Weld, 2008). Learning personal assistants learn how to help users by observing them perform tasks, and taking over where possible (Faulring, Mohnkern, Steinfeld, & Myers, 2008; Freed, et al., 2008; T. Mitchell, Caruana, Freitag, McDermott, & Zabowski, 1994; Segal & Kephart, 1999; Steinfeld, Bennett, et al., 2007; Steinfeld, Quinones, Zimmerman, Bennett, & Siewiorek, 2007). Critique-based recommendation systems work as a partnership between users and the system where until an acceptable recommendation is offered the user continues to make their preferences and requirements more explicit (Averjanova, Ricci, & Nguyen, 2008; Reilly, Zhang, McGinty, Pu, & Smyth, 2007; Ricci & Nguyen, 2007; Zhang, Jones, & Pu, 2008). Adapting to situational impairments means sensing factors in the user context that may impose adverse or uncommon temporary "disability" (e.g. low lighting, physical activity, or cold fingers) and adapts the user interface to appropriately (Barnard, Yi, Jacko, & Sears, 2007; Kane, Wobbrock, & Smith, 2008; Lin, Goldman, Price, Sears, & Jacko, 2007; MacKay, Dearman, Inkpen, & Watters, 2005; Mizobuchi, Chignell, & Newton, 2005; Mustonen, Olkkonen, & Hakkinen, 2004; Oulasvirta, Tamminen, Roto, & Kuorelahti, 2005; Pascoe, Ryan, & Morse, 2000; A. Sears, Lin, Jacko, & Xiao, 2003; Vadas, Patel, Lyons, Starner, & Jacko, 2006). User interfaces that adapt to the current task modify the presentation and organization of a user interface based on a prediction of the user's next task (Findlater & McGrenere, 2004, 2008; Findlater, Moffatt, McGrenere, & Dawson, 2009; Gajos, Czerwinski, Tan, & Weld, 2006; Gajos, Everitt, Tan, Czerwinski, & Weld, 2008; J. Mitchell & Shneiderman, 1989; Andrew Sears & Shneiderman, 1994).

This categorization offers a useful framework for investigating and understanding the current systems in usage and in development. All of these have associated benefits and tradeoffs and serve different purposes. Across all of these methodologies, including hybrids amongst them, many of the same opportunities to make personalization more personal exist.

Richness of Dataset for Recommendations

Another key factor that has tremendous impact on a personalized recommendation engine's ability to properly match users with appropriate content is the sheer amount of data available for the system to draw upon. Larger datasets improve the quality of the recommendation algorithms' results (Burke, 2002). For example with larger data sets collaborative filtering systems can better match a user with similar users. Similarly with a content-based recommender a larger data set enables the system to better match a user's preferences with the association features of a product. With an existing larger data set in place the system can avoid the cold-start problem, which poses a daunting challenge when new items or new users without any ratings are encountered.

The positives stemming from a larger dataset are obvious, but the interaction between the size of this data and each of the recommendation approaches outlined above is unknown. For example if little background data is available to the recommendation engine about the user and a new piece of recommended content it is not clear whether it would be better to employ a demographic or a content-based recommender in terms of the user's satisfaction with the output and perceptions about the quality of the system. It is unclear if this decision is the same when the dataset powering the recommendation algorithm is sizable. Investigating the role of the amount of data used as the basis of the personalized system's offerings is a future direction for researchers looking to improve personalization at this step in the process.

Type of Product or Service Recommended

Additionally the interaction between the size of the dataset and the type of product or service recommended is an important topic for future research to address. Adding to the previous example, it is unexplored which recommendation approach to select given the limited available dataset for various product types and services. One important distinction to investigate particularly on the web in terms of its impact on the selection of the recommendation algorithm and size of the dataset, is whether the product is a *search product* or an *experience product* (Klein, 1998; Nelson, 1970, 1974, 1976, 1981). Search goods (e.g. cookware, house furnishings, carpets, cameras, garden supplies, and clothing) are products which full information can be assessed prior to purchase. On the other hand, experience goods (e.g. food, drugs, toiletries, books, television, and household appliances) are products which full information cannot be determined prior to purchase without actually using it. Investigating these and other product types are important areas for future research aiming to advance the personalization process and specifically affect the matching user with appropriate content stage.

This section offered an overview of the various recommender system approaches and some key considerations based on the data available for the recommendations and product or type of service being recommended. The next step is for researchers to investigate how the intersections play out in terms of how optimal the resulting recommendations *seem* to users, irrespective of their actual quality. These empirical findings will provide designers with a clear roadmap for deciphering what recommendation approach to select to take advantage of the affordances offered by the digital age and make their personalized offering feel more personal.

PRESENT PERSONALIZED CONTENT

Before reaching this phase in the personalization process cycle the system to some degree has formulated an understanding of the consumer and matched them with appropriate available content. Much like the video rental store clerk or owner, the personalized system knows the customer and has handpicked recommendations just for them. At this stage in the personalization process the recommendation system is ready to present the personalized content to the end user.

Returning back to the local video store analogy, the store clerk or owner does not simply hand off the recommended titles once they have been selected to the customer. They present the personalized content appropriately by framing the recommendation in the context of the individual's past likings and profile. These same principles for presenting personalized content apply for adaptive systems on the web, mobile phones, and desktop computers in Digital Consumerism. Acting like the personalization process is complete once matching content is found by these systems and services would be like a store clerk abruptly handing a regular customer a video and walking away. For personalization to feel truly personal and fully leverage the power of new media technologies, it is critical for these systems to properly situate and position their personalized offerings.

One of the biggest issues with personalization systems is that they operate like a black box; users are unaware of what computer systems think about them and how this information is being used. In general current instantiations of these systems violate one of Nielson's key usability principles concerning system mistakes (Jakob Nielsen & L. Mack, 1994), which prescribes good interface to *help users recognize, diagnose, and recover from errors*. Regardless of how advanced they are, personalized systems in this stage of media evolution and algorithm design will make mistakes some percentage of the time. If systems never reveal their mistake to users at some point during their interaction, users will presumably have a frustrating experience stemming from a difficulty diagnosing and recovering from the system's error.

The consequences of not clearly presenting recommendations can be disastrous. This is evidenced by an anecdote about a TiVo (Li & Kao, 2008) user who is confused about why his TiVo seems fixated on recording programs with homosexual themes, concludes that his TiVo mistakenly thinks he is homosexual, tries to correct this mistake by watching "guy stuff", but ends up overcompensating and getting recommendations all about wars and the military (Zaslow, 2002). There is a wealth of relevant literature from HCI to draw from, namely for framing the recommendation, offering it at the right time, and ranking it appropriately, to improve the personalization process cycle at this step of presenting personalized content to avoid the poor user experiences detailed in this anecdote.

Feedback and Transparency

An underlying HCI principle for good user-centered design is that interfaces must always keep users informed about background system processes. Proper system feedback for users is frequently highlighted as a design necessity (Norman, 1990). Abiding by this principle entails giving user actions an immediate and obvious effect. Applying this design principle to this stage in the personalization process means clearly informing users about why a particular recommendation is tailored to suit their individual needs by clearly explicating the connection to their unique interests and history.

Nielsen's widely used ten usability heuristics for guiding good user interface design also stress the need for appropriate *feedback* (J Nielsen & Mack, 1994). The first of ten design rules of thumb, *visibility of system status*, encourages interface designers to always keep users aware of what the system is doing by providing appropriate feedback in a timely manner. Applying this heuristic to this stage in the personalization process entails these systems keeping consumers aware of its thought processes and how it has arrived at a specific recommendation or tailored effect for each individual.

The broader design principles regarding system feedback encompass the personalization research area of explanations (Tintarev, 2007; Tintarev & Masthoff, 2007a, 2007b). Tintarev and Masthoff's framework for good explanations for personalized recommender systems includes six aims: 1) *transparency*- explaining how the system works, 2) *scrutability*- allowing users to tell the system it is wrong, 3) *effectiveness*- helping users make good decisions, 4) *persuasiveness*- convincing users to try or buy, 5) *efficiency*- helping users make faster decisions, and 6) *satisfaction*- increasing the usability or enjoyment. The transparency, scrutability, effectiveness, efficiency and satisfaction aims are closely tied to Norman design principle of feedback (Norman, 1990) and the relevant aforementioned Nielsen heuristics. These enumerated aspects of good explanations are critical for designers to think through when presenting personalized content. The fourth goal of good explanations persuasiveness taps into the rich domain of persuasive technology (Fogg, 2002). The detailed lessons learned from the broader domain of persuasion and influence (Cialdini, 2008; Petty & Cacioppo, 1996) and benefits for this stage of the personalization process are beyond the scope of this chapter, but important for improving user experiences when presenting personalized content.

According to Herlocker et al. (2000), having an explanation that provides transparency on how the recommendation system works is beneficial for users in several key ways: 1) *Justification*- Explanations provide justification and reasoning for a recommendation, allowing users to decide how much confidence to place in the recommendation. This relates to transparency as detailed by Norman and Tintarev and Masthoff. 2) *User Involvement*- Explanations increase user involvement, allowing users to complete the decision process with their own knowledge. This benefits personalized systems by making them more engaging for users, which is a chief design aim producers in any media space. 3) *Education*- Explanations educate users on the processes used to generate limitations. 4) *Acceptance*- Explanations make the system's strengths and limitations, as well as justifications for suggestions, fully transparent, leading users to greater acceptance of the recommendation system as a decision aid (Herlocker, Konstan, & Riedl, 2000). These two final ways are relevant to the Nielsen heuristic of helping users diagnose and fix errors.

Empirical work in the domain of transparency for improving personalized recommendation systems and more broadly Digital Consumerism, is limited in sheer number of studies and methodology. However, the following work offers a valuable starting point and initial angles for designers to utilize and researchers to pursue.

Herlocker et. al (2000) conducted two studies investigating how best to explain collaborative filtering recommendations for the MovieLens personalized movie recommendation system (Herlocker, et al., 2000). In the first study surveying 78 people they explored how users would respond to various explanations derived from the framework enumerated above. Out of the 21 explanation interfaces tested the best movie recommendation explanations used histograms of the neighbors' ratings, past performance, similarity to other items in the user's profile, and favorite actor or actress. In the second study 210 people were surveyed in this same context to determine whether adding explanation interfaces to a collaborative filtering system would both improve user acceptance of the system and their filtering decisions. According to the exit interviews and qualitative feedback, participants liked it when explanation interfaces were added to MovieLens, but its impact on their filtering decisions was inconclusive from this study.

Cramer et. al (2008) investigated the effects of transparency on trust in and acceptance of personalized recommendations in the context of an user-adaptive art recommender by comparing the impact of three different types of explanations: 1) no transparency, 2) an explanation of why the recommendation had been made, and 3) a rating of how confident the system was that the recommendation would be interesting to the user (Cramer, et al., 2008). The key relevant result of this study indicated that explaining to a user why a recommendation was made increased its acceptance over not having any transparency, but not trust in the system itself. Additionally, showing how certain the recommender was in the recommendation did not influence trust and acceptance.

A user study of 12 people by Sinha and Swearingen (2002) with five music recommender systems making 10 recommendations each suggested that users like and feel more confident in recommendations from transparent systems and they like to know why something was recommended to them by the system even if they already like it (Sinha & Swearingen, 2002). The main design implication from Sinha's user study was that it is not enough for a system to just be accurate; it also needs to reveal its inner logic to its users and let them know why a particular recommendation was thought to be suitable for them.

Taken together this empirical research provides a starting point for work in this area, but it remains mostly an unexplored fertile territory from an empirical standpoint with critical design implications for media theorists and designers left to be discovered. The two studies conducted by Herlocker and colleagues offer support for the importance of transparency in personalized recommendation systems and some possible ways to attain this, but need further investigation in different contexts (Herlocker, et al., 2000). The single variable study design of Cramer et. al does not answer questions about how transparency interacts with key dimensions that frequent the real world, such as fixed and ephemeral aspects of the user and the type of content recommended (Cramer, et al., 2008). The exploration by Sinha is limited by small sample size and it being a user study, rather than a controlled experiment (Sinha & Swearingen, 2002).

Making the inner workings and algorithms of personalized systems transparent to users is a rich topic deserving of much more empirical attention. It remains mostly an unexplored fertile territory with critical design implications for media theorists and designers left to be discovered. A useful framework for continuing the investigation of this topic is revealing a person's states and traits. States include such static aspects of a person such as their age, gender, race and ethnicity, while traits are more ephemeral aspects of a person such as their mood, emotion, and delectation. By utilizing this framework, personalized systems can take advantage of the capabilities of the Digital Consumerism to offer a personalized experience, which acknowledges each individual's unique needs, that was simply not possible in the era of Mass Consumerism. Properly personalized media interfaces particularly in terms of transparency and feedback make every individual feel like the star of the show as the entire media experience is centered on them, regardless of their age, gender, race, religion, socioeconomic status, or even their present affective state.

By profiling, understanding, and appropriately responding to each individual's traits and states, personalized systems create new opportunities. Social groups that have been overlooked and mischaracterized by traditional mass media can now feel as though the permanent and transient aspects of their identity are important, relevant, and considered in their new and more powerful relationships with personalized media. Much like other aspects of the evolution of consumerism within the context of media change, framing and optimizing personalization affords many new advances for consumers to take and feel in control of their increasingly media-centric lives. A full set of design guidelines for personalization based on each of these specific states and traits are currently lacking and offer a new opportunity for researchers interested in advancing this space.

Uncovering transparency guidelines for presenting personalized content has the added benefit of helping users formulate a proper conceptual model (Norman, 1990) of the system. This helps with iteration, improving and refining the recommended output, as the user knows how and what to change about their interactions with the system at the gathering information stage. Additionally this helps the user comprehend how the system uses his or her information at the building and matching stages of the personalization process. The summation of increased user knowledge for these three phases of the personalization cycle helps revive the handshake, the golden standard for customer service.

Timing

In addition to feedback and transparency another way to work towards replicating the symbolic handshake at this stage in the personalization cycle is to present the personalized content at the appropriate time. At the video store the store clerk or owner would wait for the opportune moment to give the customer their personalized recommendation; not interrupting their other activities and using an appropriate transition before making the delivery. It is important for designers of systems for Digital Consumerism to replicate this very same step at this stage in the personalization process.

Panayiotou et. al (2006) detailed the importance of time based personalization, particularly for mobile users equipped with handheld devices (Panayiotou, Andreou, & Samaras, 2006). Mobile user needs are dependent on their context, which is a function of both time and activity. Augmenting user profiles with personalized time metadata enables personalized systems to more appropriately weight user interests with respect to time-zones and ongoing experiences. Panayiotou et al implemented a prototype and their early stage evaluation showed promising results for improving personalization by taking into consideration a user's time based needs.

The importance of proper presentation interval is illustrated in a web experiment conducted by Rao et. al 2009, where altering the presentation intervals of poor dating matches in a personalized online dating recommender affected user frustration levels (Rao, et al., 2009). Specially, participants were more frustrated with the recommendation system when it gave the poor dating matches sequentially, rather than all at the end. In essence seeing no adaptation or improvement repeatedly was frustrating for the participants compared to seeing all the poor results in one final assemblage. The key relevant design implication from this aspect of this study is to avoid continuously showing poor recommendations when possible as opposed to presenting them as a singular collection. This result also illuminates the need for proper transparency and feedback to help people decipher recommendations as well as a mechanism for users to immediately explicitly comment on the results provided.

The various effects of properly timing the presentation of personalized content are an under-researched, yet important area in personalization. Panayitou 2006 and Rao et al 2009 offer a launching pad for investigations in this space (Panayiotou, et al., 2006; Rao, et al., 2009). A future direction for researching timing in recommendation presentation is more rigorous evaluation about how to utilize time-based knowledge about an individual user appropriately within the context of their daily lives. Another direction is looking at the effects of varying presentation intervals for both good recommendations and other domains beyond dating matches. It is also potentially important to give consumers the opportunity to access the recommendations when they feel so inclined (e.g., the value of periodicity in library rental and renewal schemes).

Ranking and Quantity

Transparency and feedback guide *how* to present, timing deals with *when* to present, and ranking in the case of multiple recommendations concerns *what order* to present. Revisiting the video store analogy when the store clerk is ready to present the recommendations if there are multiple items, to offer a truly personalized experience, they order them in a sensible manner with respect to both ranking and quantity.

With the advent of the web and the ubiquity of the digitized content it became critical to associate a rank with each chunk of information and present them accordingly. Google's web search and associated Page Rank exemplify this concept; web pages across the entire World Wide Web are indexed, ranked, and presented in an intelligent order with respect to a user's search query (Sergey Brin, 1998; Sergey Brin, Motwani, Page, & Winograd, 1998; S. Brin & Page, 1998). Ranking is a major advancement of the digital era as it enables personalized ordering and packaging of content. For example, one basketball fan may prefer to see all NBA video clips first and then NCAA clips, while another may prefer the opposite. Such tailoring for each individual consumer at the level of ranking and ordering content was simply not possible in the era of Macro Consumerism where mass production and delivery was such a critical component for success, because of the major resulting time inefficiency. In the age of Digital Consumerism however it is attainable.

The Gricean conversational maxim of *quantity* stresses making the contribution as informative as required and not excessive (Grice, 1975). Much in the same way it is important for recommendation systems to not overwhelm their users with content during the presentation stage. At the video store the store clerk might have hundreds of movies that they think a customer might like, but they only present them with a few carefully selected titles at once. Similarly on a web search engine like Google even though there are often hundreds, if not thousands of search results for popular queries, by default only the top ten results are displayed (Weld, et al., 2003). It is important for designers of personalized recommendation systems to resist the temptation to offer too many recommendations given the oftentimes plethora of available content and the ease with which to suggest it in the digital age.

Personalized ranking of content has been an area of much interest for researchers and is evident in the ongoing work on personalized web search (Ark, Dryer, & Lu, 1999; de Vrieze, van Bommel, & van der Weide, 2004; Picard). In the coming years research in this space should only expand. Another key future direction for research in this space is investigating the intersections between the number of recommendations to present for various domains and each user's corresponding state and traits. A person's static mental capacity as well as their context can heavily impact how many recommendations they can handle before running into the problem of cognitive overload (Kirsh, 2000). It is critical for interfaces in this Digital age of consumerism to continue to investigate ways to intelligently account for these individual factors in this stage of the personalization process.

CONCLUSION

By building upon the lessons learned from Micro and Mass Consumerism, HCI, and social science with respect to the four-step personalization process outlined and explored in this chapter- 1) Gather user information and needs, 2) Build user model and profile, 3) Match user with appropriate available content, and 4) Present personalized content)- Digital Consumerism particularly in the domain of personalized recommendation systems can radically advance the user experience. For designers working within this space, utilizing the design guidelines at each of these four phases will aid in the production of interactions that more closely approximate the handshake, which symbolizes the gold standard for customer service. For researchers and media theorists the abstracted key aspects of personalization illuminate future directions for inquiry and how to contextualize this work within the larger master goal of improving the interpersonal relationship between retailers and consumers. This framework offers a common ground for all of the diverse communities working within the fields of consumerism and personalized systems to work together towards the continued progression of reviving the friendly handshake of Micro Consumerism without losing the benefits of Macro Consumerism in this technologically rich stage of media evolution.

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