First and Last Mile Problems in the big data settings

Jaeyeop Chung [redacted]

MSc Data Engineering and Analytics, Technical University of Munich , Germany

jaeyeop.chung@tum.de

1. Introduction

The term ***nudge*** has emerged and gained its popularity with the Sunstein & Thaler's Book "*Nudge: Improving Decisions About Health, Wealth, and Happiness*". The concept of nudging is to help people make better decisions "*without forcing certain outcomes upon anyone*", given the decision environment-choice architecture(Thaler & Sunstein, 2008). However, this type of nudge could not be effective as its popularity due to the heterogeneity problem (Thaler & Sunstein, 2008), in which an identical nudge is applied to the heterogeneous populations. With the widespread of online environments, flooded with data from everyday tasks, and high-performance devices, it has been enabled to cope with the heterogeneity problem; **personalized nudge**. This term was advanced and coined as **hypernudge** by Yeung (2016). Hypernudges are also known as **data driven decision nudges** or **recommender systems** (Lanzing, 2018).

Nudges, either as the traditional nudges or hypernudges, don't automatically change the people's behavior, rather they serve as a guidance, not an actuator. Nudges can even trigger unexpected behavior that is not beneficial to the targets (Sunstein, 2016). Several behavioral models have suggested frameworks to trigger the expected behaviors such as **Fogg behavior model** (Fogg, 2009). What Fogg model suggests is that actions can only be triggered when one goes beyond a threshold. This challenge for nudges to push users beyond the threshold and to trigger behavior changes is called "**The Last-Mile Problem**" (Guszcza, 2015). To solve the problem, we have to consider the problem not only from behavioral science but also from implementation perspective. Guszcza (2015) puts, "*Regardless of application, the implementation must be successful in two senses; First, the model must be converted into a piece of software that combines data and produces a useful prediction. Second end users must be trained to understand, accept and act upon the indication*". This gives us a room to break down the last-mile problem into subproblems; algorithmic level nudges(Yeung, 2016) and user interface(UI) level nudges(Thaler & Sunstein, 2008; Weinmann et al., 2016;).

The fact that traditional nuding and hypernudging techniques both operate based on cognitive biases(Mitchell, 1997; Thaler & Sunstein, 2008) raises the ethical issues in the sense both techniques are devised to reduce the choices so that the applications can ultimately guide people for their own good(Yeung, 2016; Guszcza, 2023). However, one might have experienced receiving unwanted advertisement mails or subscribing to paid-services by clicking the uncolored button on a pop-up message taking it for granted that the uncolored button is to reject/cancel, or by clicking check boxes under the terms of conditions when signing up for a website. These malicious UI design tricks to manipulate users are referred to as dark patterns(Sin et al., 2022). Because of the fact that those dark patterns are usually implemented through traditional nudging techniques, the dark pattern problems can be mitigated by regulations(Nouwens et al., 2020). However, hypernudging techniques can not easily be resolved just by regulations because hypernudging techniques are used to generate unseen data(Mitchell, 1997; Yeung, 2016). Thus, depending on which data we use, the systems can show immoral behaviors, not being able to provide appropriate guidance. This choice of the right data is called "**The First-Mile Problem**"(Guszcza, 2023).

Breaking down such system into subproblems can give us advantages. Firstly, There are many acknowledged papers that analyzed the effectiveness of traditional nudges(Caraban et al., 2019; CMA, 2022), Secondly, we can separate personalizing algorithms from the whole system and leverage them as a part of choice architectures(Jameson, 2014).

This essay is an attempt to systematically approach the last-mile problems in the big data settings, especially in recommender systems, by breaking the problems into subproblems, and will try to apply the different types of nudges and choice architectures accordingly. To do so the essay will introduce (1) building blocks to approach the last-mile problem by defining the traditional nudge and hypernudge (2) Last-Mile Problem (3) First-Mile Problem and ethical issues that come along.

Keyword: Traditional Nudge, Hypernudge, Recommender System, Choice Architecture, Last Mile Problem.

2. Traditional nudge and hypernudge

2.1 Traditional nudge

The term, **nudge**, by definition, deals with any aspect of choice environment that alters people's behaviour (Thaler & Sunstein, 2008). This nudge mainly operates in offline *context* in the public field such as environment or public policies (Weinmann et al., 2016). In the recent years, with the advance of digital technologies, many of decisions are made through online interactions ranging from e-governments to e-commerce (Weinmann et al., 2016). **Digital nudge** is the "*use of user-interface design elements to guide people's behaviour in online choice environments*" (Weinmann et al., 2016). The difference between two nudges is whether the choice environment is the venue where the interventions take place; online and offline. In that sense, I will use **traditional nudge** to refer to nudge defined by Thaler and Sunstein (2008) and digital nudge defined by Weinmann et al. (2016).

2.2 Hypernudge and recommender system

The term, **hypernudge,** is first coined by Yeung (2016), but the definition is not straightforward to adopt. Mills (2022b) gives a clearer definition; "*Hypernudges describes a group of phenomena at the intersection of behavioral science and computer science*", "*Hypernudges are defined as a system of* *nudges which change over time and in response of feedback*". That is hypernudge is a system/algorithm level nudge that can change over time, thus can deal with the heterogeneity problems (Yeung, 2016). Mills (2022b) points out that hypernudge can be used as an umbrella term for digital nudge, which is reasonable as most of online environments are built on top of algorithms. In my essay, I assume that it is a superset to digital nudge for its dynamic/algorithmic characteristic. During my research, the term hypernudge appeared as an umbrella term not only for digital nudge, but also for other types of nudges such as **autonomous nudge** (Mills, 2022a), **smart nudge** (Mele et al., 2020), and **personalized nudge** (Mills, 2020), which are built on top of or a part of hypernudges. Lanzing (2018) sees hypernudge as **recommender system**.

For the purpose of my essay, I will differentiate digital nudge and hypernudge in the sense that hypernudge can be seen as an algorithmic part that produces the predictions, while digital nudge can be considered as an UI design to present the predictions. Otherwise, I will use interchangeably hypernudge as a superset of other types of abovementioned nudge-autonomous nudge, smart nudge, personalized nudge, and recommender system.

3. Choice Architectures : Traditional vs Hypernudge

Choice architectures can be considered as a design in which options and choices are presented to target populations. A choice architecture is particularly important to elicit behavior changes as this is the step to choose the type of interventions with the target population (Thaler & Sunstein, 2008).

3.1 Traditional choice architecture

In the traditional settings, choice architectures can be considered as a design in which options and choices are presented to target populations. The choice situation consists of three steps; given the choice structure, the target digests choice information, and nudges give implicit pressures on targets to make a choice (CMA, 2022). For example, when you are shopping at a REWE supermarket at München Hauptbahnhof, how the items are displayed is the given choice structure. You are unconsciously pressured to choose the items on a shelf in a way a choice architect designed. This is a type of choice structures of nudge suggested by [Nudge Book]. In the online settings, for example, on REWE online shop, UI plays the role; a choice structure of digital nudging (Weinmann et al., 2016). This type of choice environments given online is called Online Choice Architecture(OCA). As most of interventions are delivered through online(Caraban et al., 2019), and CMA (2022) refers to the taxonomy of choice architectures suggested by Münscher et al. (2015) to describe OCA, it is a reasonable approach to combine both types of choice architecture into the **traditional choice architecture**.

3.2 Hypernudge/Recommender System Choice Architecture

In the big data settings, the algorithm behind the user interface that is designed to generate personalized items -items you put on the shelf/on the UI- can also be considered as a choice structure

(Jameson, 2014; Shin & Ahmad, 2023). For example, data from Facebook's feed can be considered a hypernudge choice architecture as the most likely relevant feeds are suggested users by the Facebook's algorithm based on what it predicts will maximize the number of clicks on the posts (Shin & Ahmad, 2023). Unlike the traditional choice architectures, it was difficult to find hypernudge choice architectures as structured as Münscher et al., (2015). The difficulty of this section was that many of researchers did not distinguish the choice architectures between the traditional nudge and hypernudge choice architectures (Jesse & Jannach, 2021) or focused on the ethical issues of hypernudges (Mills, 2022a; Yeung, 2016). It was not also clear whether to see recommender system as a choice architecture (Jameson, 2014) or as a choice architect (Jesse & Jannach, 2021).

Jameson (2014) suggests an answer to the above ambiguities. The purpose of Jameson (2014) is to support choice architects to choose the effective form of recommender systems with the ASPECT and ARCADE framework. The ASPECT model is an answer to "how do people make choices?" by describing 6 choice patterns. The ARCADE model is an answer to "how can choice architects help people make better decisions?" with 6 high-level strategies. Figure 1, Table 1, and Table 2 briefly describe the framework. The details are described in the author's book "*Choice Architecture for Human-Computer Interaction*" (Jameson, 2013). In a nutshell, the ASPECT model is the expected behavior of users using the system and the ARCADE model is a combination of the effective interfaces to each choice pattern and technologies that support interfaces to support the users' choice environments. The framework can be used by choice architects in the following steps: choice architects (1) takes into his/her considerations the expected choice behaviors using the ARCADE model (2) consults the ARCADE model to decide how to present the items(predictions) (3) chooses the appropriate algorithm (Jameson, 2014). These steps can be thought of 2 steps: (1~2) as choosing the traditional choice architecture, and (2~3) choosing the hypernudge choice architecture. This framework suggests a possibility to formulate the existing/emerging hypernudge choice structures and implication that my re-grouping of nudges into traditional and hypernudge is a legitimate approach.

5. Last-Mile Problem

In many cases, when seeing a problem as a third party, most of time, determining the appropriate action is straightforward. For example, if someone sees obnoxious pictures on cigarette packs, we may easily assume that the message will be clearly delivered and make people to stop smkoing. However, in many situations, such a message serves as a more or less suggestion but does not prompt the desired behavior changes. Some nudges might mitigate one problem but aggravate another problem. A few might be persuaded by the campaign, but the majority might not be affected at all. The same also applies to online environments. To improve the effectiveness of the nudges, we can leverage the power of big data and provides each individual with personalized suggestions (Yeung, 2016).

Jameson (2013) puts, a good choice architecture for human-computer interaction (HCI) must answer two questions; *"(1) How do people make choices in their everyday lives, with or without computing technology? (2) What are the general ways in which it's possible to help people make better choices; and how can these be applied in the context of interactive computing technologies?*". This is a complicated problem in that we not only have to consider how the target populations would react to our system, but also have to consider algorithms that can support to derive the desired changes of behaviors. The problem of coherently connecting these two components is called the **last-mile problem** (Guszcza, 2015; 2023).

This essay has re-defined traditional nudge and hypernudge and bounded each nudge; traditional nudge as a static design in either offline or online environments, through which target populations directly interact with the interventions; hypernudge as an algorithmic level of nudge that can dynamically adapt to heterogeneity and support the user interface. For example, we can think of hypernudges as a type of a programmed online application such as Netflix, which has a back-end and front-end because most of nudges operate in online settings (Caraban et al., 2019). The separation of the traditional and hypernudge choice architectures in the previous sections enables it to apply these two different nudges to the application architecture; the traditional choice architectures can be applied to the front-end; the hypernudge choice architectures can be applied to the back-end. The advantage of doing so is that we can conveniently, but coherently, redesign each part of the program and adapt to the target populations, by leveraging already existing articles that have analyzed the nudging techniques and their estimated effectiveness.

Caraban et al. (2019) has analyzed 23 ways of traditional nudging techniques and CMA (2022) has comprehensively analyzed the nudging techniques and their effectiveness based on a choice architecture taxonomy (Münscher et al., 2015). These articles are widely acknowledged in the nudging community. The social scientist scientists or designers can analyse and make use of the human biases and other factors that can affect their outcomes the most, based on these taxonomies, or further studies based on these articles. This step well algins with the traditional concept. On the other hand, based on the interface of the applications, in the form of either offline nudges or digital nudges, programmers or data scientists can develop the algorithms that can best service the design. Although there were not acknowledged taxonomies in hypernudge choice architectures as Münscher et al. (2015), we can think algorithms as a separate part of the system that can support the traditional nudges. For example, ASPECT and ARCADE frame work(Jameson, 2014) can be an option. From the Fogg behavior model, we can also view this structure as adjusting one's ability and motivation. Traditional nudges can be used to simplify the task, to remind the task, or to increase motivation(Caraban et al., 2019). However, choice of algorithms that can best support each traditional choice architecture is also important in the big data settings in the structured manner, which has not yet been studied broadly.

The 2012 US presidential campaign, the first big data election, makes a good example of this separation (Guszcza, 2019). The Obama campaign team identified the voters being likely to be pressured to vote for Obama instead of likely Obama voters, which could minimize the reactance from the people who are already in favor of us, and increase the number of ballots from the potential advocates. After identifying the targets, they chose a nudging technique that they asked for these identified target populations to sign commitment cards adorned with a photo of Barack Obama, which was based on the psychological studies that people will be more likely take things into action when a sense of responsibilities is posed upon them. We can consider the steps so far are the traditional steps. On the contrary, the choice of algorithms to determine these target populations, or modelling algorithms can be considered as the choice of hypernudge choice architecture that can support best the traditional steps. The strategy was successful, Although Guszcza (2015) did not mention about detailed tools we can use to improve the nudging effectiveness, as introduced in the previous section, by looking at the problem in two layers, we can simplify problems and improve the likelihood of the campaign by choosing the tools from, for example, CMA (2022) for traditional nudges and Jameson (2014) for the hypernudges. The take away from 2012 US presidential campaign example is that the Obama's campaign team explicitly separated the behavioural nudge tactics from algorithm tactics and that this strategy can be applied to a variety of distinct domains.

6. First-Mile Problem

Guszcza (2023) raises another problem, the **first-mile problem;** "*The first-mile problem is that you can't just grab whatever data is convenient – regardless of how "big" it is. Rather, you must design the right dataset, and doing so usually has lots of ethical and domain-specific nuances. Typically it's more of a social science challenge than a computer science challenge".* This problem of choosing the right data set is complicated. Unlike in traditional settings, where we are dealing with visible options at present, hypernudging techniques are used to produce unseen data based on the historical data (Mitchell, 1997). The ethical problems such as dark patterns and data privacy problems, which are realized by maliciously designing UI, have been able to be mitigated by the efforts of governmental entities to enforce regulations (Nouwens et al., 2020). However, whether the hypernudging applications can assists' users is not deterministic in the black box manner, depending on the data choice architects choose. In this sense, the first-mile problem can be seen as an extension to or on the same line with the AI ethical issues, and converges to responsibility problem (Mills, 2022a).

Depending on which data the choice architects' choose, his or her subconscious biases are also fed into the data, in addition to the preexisting biases in the data. As Tom Mitchell puts, data-driven applications learn the patterns from historical data and generalize them to predict unseen data, which makes the applications vulnerable to biases. It is difficult to pick out what is biased and what is not biased in our data as human biases are subconsciously ingrained in our society. COMPAS, a tool used by courts in the US, which was biased against African-Americans (Angwin et al., 2016) and A-level grading system that discriminated the marginalized students (The Guardian, 2020) show the consequences of the biased data.

The central problem of this type of applications, which some might call "autonomous nudge" (Mills, 2022a), is that it is difficult to identify a part of the application that led to the undesirable predictions because the development process is not a single cycle process but involves multiple intertwined interaction process between the front-end and back-end; On the front-end, social scientists and other domain excerpts are involved in the process of deciding the optimization strategies and UI designs-the traditional choice architecture; On the back end, data scientists build the predictive models based on the sketch from the front-end-hypernudge choice architecture. This creates the responsibility problems among the choice architects, which Mills (2022a) calls it "*the responsibility gaps*". For example, ChatGPT has been found prone to misinformation for its incapability of discerning the boundaries between the fact and likelihood. Because of its easy accessibility and ability to confidently reply, there is a possibility that the misinformation spreads quickly within the society. It is difficult question to answer who should take responsibility for it.

Responsibility in AI settings can't be mentioned without explanability and transparency. One way to achieve these ethical metrics is suggested as explainable AI (Christoph Molnar, 2019), for example, by letting the algorithm visualize how they reached the outputs (Ahn & Lin, 2019). Another way is to explicitly explain how the algorithms work to the target populations (Möhlmann, 2021). Such strategies can help stay within the ethical and legal boundaries such as GDPR, but cannot still give an answer to the first mile problem.

7. Summary and Conclusion

The nudging is used as a bridge between the predictive analytics and the desired change of behaviors. social scientists or designers are working in the frontier of the applications designing the effective interface (offline or online) with the users, while data scientists work behind the scene to develop models to assist the desired results of the overall process. Existing nudging techniques can be seen with the same logic. The traditional nudges are the ones the members in the frontier use to equip the application from design perspective, while hypernudges are the ones the support unit in the rear supplying the frontier unit in forms of algorithms. While traditional choice architectures have been broadly studied and analyzed, the number of articles on hypernudge choice architecture was limited and most of them were focused on the performance spectrum.

However, we have seen from the 2012 US presidential campaign example seeing behavioral tactics separately from algorithmic tactics can help approach the last mile problem systematically. In the article, I introduced (CMA, 2022) and (Angwin et al., 2016) as examples for the traditional nudge tools, and (Jameson, 2014) as a tool that can be used in the recommender system settings. Although further researches is inevitable to prove the validity of my approach due to the broad range of the topic, some articles(Jameson, 2014; Shin & Ahmad, 2023) implied a potential that, with more efforts to analyze the application techniques in the big data settings, this approach also can be structured similar to the taxonomy of Münscher (2015).

Lastly, I mentioned the first-mile problem in the big data settings. Unlike, last-mile problems, my approach showed a limitation because the selection of the right data entails complicated processes and interactions between the front-end and back-end people. From ethical perspective, regulations such as GDPR or EU AI Act can mitigate the problems of traditional choice architectures such as dark patterns, but they can act as more or less than a guideline for the nudging applications in the big data settings. What many articles often so every agree on the first mile problem is the human-in-the-loop process (Shin & Ahmad, 2023), which suggest that not only the choice architectures but also data should be adapted to the environment accordingly.

The essay covered a wide range of topics within a limited timeframe. Many of divergent edge theories are spawning every day, thus categorizing all of the nudges into traditional nudge and hypernudge might be nuanced. However, two step approaches are well-used approaches in HCI area (Jameson, 2013). We saw the potential that this approach can simplify the nudging applications in the big data settings and facilitate effective implementation of nudges. However, the validity is still left in the questions and should be examined with the further studies.

Bibliography

Ahn, Y., & Lin, Y.-R. (2019). FairSight : Visual Analytics for Fairness in Decision Making. *IEEE Transactions on Visualization and Computer Graphics*, https://doi.org/10.1109/tvcg.2019.2934262

Angwin, J., Larson, J. (2016, May 23). Machine Bias. *ProPublica*. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Caraban, A., Karapanos, E., Gonçalves, D., & Campos, P. (2019). 23 Ways to Nudge. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* - CHI *'19.* https://doi.org/10.1145/3290605.3300733

Christoph Molnar. (2019, August 27). *Interpretable Machine Learning.* Retrieved from https://christophm.github.io/interpretable-ml-book/

CMA. (2022, April 5). Evidence review of Online Choice Architecture and consumer and competition harm. Retrieved from https://www.gov.uk/government/publications/online-choice-architecture-how-digital-design-can-harm-competition-and-consumers/evidence-review-of-online-choice-architecture-and-consumer-and-competition-harm

Fogg, B. (2009). A behavior model for persuasive design. *Proceedings of the 4th International Conference on Persuasive Technology - Persuasive '09*, *40*, 1–7. https://doi.org/10.1145/1541948.1541999

Guszcza, J. (2015, January 27). The last-mile problem: How data science and behavioral science can work together. *Deloitte Review Issue 16.* Retrieved from https://www2.deloitte.com/us/en/insights/deloitte-review/issue-16/behavioral-economics-predictive-analytics.html

Guszcza, J. (2023). Jim Guszcza Looks at AI Through the Lens of Human Behavior. *The Rockefeller Foundation*. Retrieved from https://www.rockefellerfoundation.org/bellagio-conversations-in-ai/jim-guszcza-looks-at-ai-through-the-lens-of-human-behavior/

Jameson, A. (2013). Choice Architecture for Human-Computer Interaction. *Foundations and Trends in Human–Computer Interaction*, *7*(1–2), 1–235. https://doi.org/10.1561/1100000028

Jameson, A. (2014). Recommender Systems as Part of a Choice Architecture for HCI. *CEUR Workshop Proceedings*, *1278*(1), 3-7. Retrieved from https://ceur-ws.org/Vol-1278/paper1.pdf

Jesse, M., & Jannach, D. (2021). Digital nudging with recommender systems: Survey and future directions. *Computers in Human Behavior Reports*, *3*. https://doi.org/10.1016/j.chbr.2020.100052

Lanzing, M. (2018). "Strongly Recommended" Revisiting Decisional Privacy to Judge Hypernudging in Self-Tracking Technologies. *Philosophy & Technology*, *32*(3), 549–568. https://doi.org/10.1007/s13347-018-0316-4

Mele, C., Russo Spena, T., Kaartemo, V., & Marzullo, M. L. (2020). Smart nudging: How cognitive technologies enable choice architectures for value co-creation. *Journal of Business Research*, *129,* 949-960. https://doi.org/10.1016/j.jbusres.2020.09.004

Mills, S. (2020). Personalized nudging. *Behavioural Public Policy*, *6*(1), 1–10. https://doi.org/10.1017/bpp.2020.7

Mills, S. (2022a, August 2). Autonomous nudges and AI Choice Architects – Where does responsibility lie in computer mediated decision making?. *LSE Impact Blog.* Retrieved from https://blogs.lse.ac.uk/impactofsocialsciences/2022/08/02/autonomous-nudges-and-ai-choice-architects-where-does-responsibility-lie-in-computer-mediated-decision-making/

Mills, S. (2022b). Finding the "nudge" in hypernudge. *Technology in Society*, *71*, 102-117. https://doi.org/10.1016/j.techsoc.2022.102117

Mitchell, T. M. (1997). *Machine learning*. Mcgraw-Hill.

Möhlmann, M. (2021, April 22). Algorithmic Nudges Don't Have to Be Unethical. *Harvard Business Review*. Retrieved from https://hbr.org/2021/04/algorithmic-nudges-dont-have-to-be-unethical

Münscher, R., Vetter, M., & Scheuerle, T. (2015). A Review and Taxonomy of Choice Architecture Techniques. *Journal of Behavioral Decision Making*, *29*(5), 511–524. https://doi.org/10.1002/bdm.1897

Nouwens, M., Liccardi, I., Veale, M., Karger, D., & Kagal, L. (2020). Dark Patterns after the GDPR: Scraping Consent Pop-ups and Demonstrating their Influence. *CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems,* 1-13. https://doi.org/10.1145/3313831.3376321

Shin, D., & Ahmad, N. (2023). Algorithmic Nudge: An Approach to Designing Human-Centered Generative Artificial Intelligence. *IEEE Computer*, *56*(8), 95–99. https://doi.org/10.1109/mc.2023.3278156

Sin, R., Harris, T., Nilsson, S., & Beck, T. (2022). Dark patterns in online shopping: do they work and can nudges help mitigate impulse buying? *Behavioural Public Policy*, 1–27. https://doi.org/10.1017/bpp.2022.11

Sunstein, C. R. (2016). Nudges That Fail. *SSRN Electronic Journal*, *1*(1). https://doi.org/10.2139/ssrn.2809658

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Penguin Books.

The Guardian. (2020, August 11). The Guardian view on A-level algorithms: failing the test of fairness | Editorial. *The Guardian*. Retrieved from https://www.theguardian.com/commentisfree/2020/aug/11/the-guardian-view-on-a-level-algorithms-failing-the-test-of-fairness

Weinmann, M., Schneider, C., & Brocke, J. vom. (2016). Digital Nudging. *Business & Information Systems Engineering*, *58*(6), 433–436. https://doi.org/10.1007/s12599-016-0453-1

Yeung, K. (2016). "Hypernudge": Big Data as a mode of regulation by design. *Information, Communication & Society*, *20*(1), 118–136. https://doi.org/10.1080/1369118x.2016.1186713

Appendix

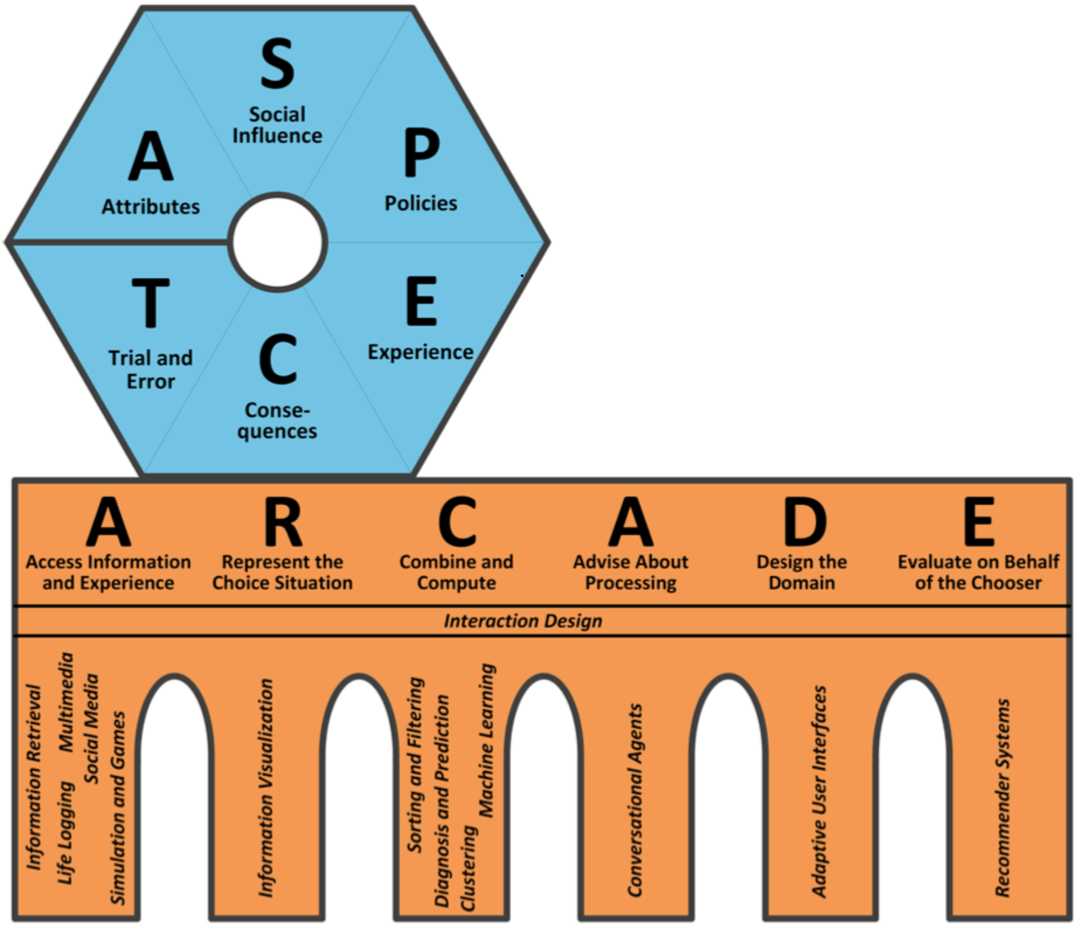

Figure 1. High-level overview of the ASPECT and ARCADE models of choice patterns and choice support strategies. (Jameson, 2014)

Table 1. Overview of the choice patterns in the ASPECT model (Jameson, 2014)

Attribute–Based Choice

Conditions of Applicability

– The options can be viewed meaningfully as items that can be described in terms of attributes and levels

– The (relative) desirability of an item can be estimated in terms of evaluations of its levels of various attributes

Typical Procedure

– (Optional:) *C* reflects in advance about the situation–specific (relative) importance of attributes and/or values of attribute levels

– *C* reduces the total set of options to a smaller *consideration set* on the basis of attribute information

– *C* chooses from among a manageable set of options

Consequence–Based Choice

Conditions of Applicability

– The choices are among actions that will have consequences

Typical Procedure

– *C* recognizes that a choice about a possible action can (or must) be made

– *C* assesses the situation

– *C* decides when and where to make the choice

– *C* identifies one or more possible actions (options)

– *C* anticipates (some of) the consequences of executing the options

– *C* evaluates (some of) the anticipated consequences

– *C* chooses an option that rates (relatively) well in terms of its consequences

Experience–Based Choice

Conditions of Applicability

– *C* has made similar choices in the past

Typical Procedure

– *C* applies recognition–primed decision making

– or *C* acts on the basis of a habit

– or *C* chooses a previously reinforced response

– or *C* applies the affect heuristic

Socially Based Choice

Conditions of Applicability

– There is some information available about what relevant other people do, expect, or recommend in this or similar situations

Typical Procedure

– *C* considers *examples* of the choices or evaluations of other persons

– or *C* considers the *expectations* of relevant people

– or *C* considers explicit advice concerning the options

Policy–Based Choice

Conditions of Applicability

– *C* encounters choices like this one on a regular basis

Typical Procedure

– [Earlier:] *C* arrives at a policy for dealing with this type of choice

– [Now:] *C* recognizes which policy is applicable to the current choice situation and applies it to identify the preferred option

– *C* determines whether actually to execute the option implied by the policy

Trial–and–Error–Based Choice

Conditions of Applicability

– The choice will be made repeatedly; or *C* will have a chance to switch from one option to another even after having started to execute the first option

Typical Procedure

– *C* selects an option *O* to try out, either using one of the other choice patterns or (maybe implicitly) by applying an *exploration strategy*

– *C* executes the selected option *O*

– *C* notices some of the consequences of executing *O*

– *C* learns something from these consequences

– (If *C* is not yet satisfied:) *C* returns to the selection step, taking into account what has been learned

Table 2. Brief explanations of the six ARCADE strategies for choice support. (Jameson, 2014)

Name of Strategy	Basic Idea
Access Information and Experience	Help *C* to gain access to information and experience that is relevant to the current choice
Represent the Choice Situation	Influence the way in which *C* perceives the choice situation in such a way that *C*'s processing is facilitated
Combine and Compute	Process available information computationally in a way that facilitates one or more processing steps of *C*
Advise About Processing	Encourage *C*, implicitly or explicitly, to apply a particular (part of a) choice pattern in a particular way
Design the Domain	Change the basic reality about which *C* is choosing so as to make the choice problem easier
Evaluate on Behalf of the Chooser	Take over from *C* some step in the processing that involves evaluation or choice among alternatives