Personal Internet Shopping Agent (PISA): A Framework

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ABSTRACT

We explore the concept of a personal internet shopping agent (PISA) that can be automated to perform shopping tasks online. PISAs, which can operate in either manual or fully automated mode, are inevitable due to increasingly sophisticated artificial intelligence applications in retailing and ongoing consumer acceptance of advanced technologies. After proposing a generic PISA model comprised of four sub-systems, we close with a brief discussion about concerns and implications arising from PISA usage.

Introduction

Non-human shopping assistance is already a fact of consumer life. In brick-and-mortar stores, consumers are increasingly comfortable shopping with robot companions (Bertacchini, Bilotta, & Pantano, 2017). Online, many consumers rely on recommendation engines and shopping agents to speed shopping tasks and minimize cognitive overload (Aljukhadar, Senecal, & Daoust, 2010). These examples illustrate consumers' relentless efforts to simplify their lives by semi-automating repetitive and tiresome shopping tasks (Dawar, 2016).

Would consumers miss shopping as it has existed for more than a century? Would they willingly cede their purchase-related activities a personalized shopping agent built around a sophisticated artificial intelligence (AI) system? What would that system entail and what are its implications for consumer marketing? We now explore answers to these questions.

Shopping: Desirable or Undesirable?

For every text that extols the love of shopping—for recreation, self-expression, or youthful self-definition (Pooler, 2003; Yarrow & O'Donnell, 2009)—there is another text about apathetic shoppers (predominantly male and price insensitive (Reid & Brown, 1996)) or irrational purchase decisions (Graves, 2010). As a contrasting model of shopping vividly illustrates, shopping can both liberate and constrain 'the self' (Compeau, Monroe, Grewal, & Reynolds, 2016).

For consumers, shopping has provided utilitarian, social/psychological, and hedonic/recreational/leisure benefits. Utilitarian benefits included bargain hunting (e.g., save money, find best deal in minimal time), acquiring valued items, and reconnaissance (i.e., learn for future purchases). Social/psychological benefits included communicating wealth and power (e.g., conspicuous consumption), discovering new things, expressing/defining oneself (especially among adolescents and young adults), avoiding regret over opportunity costs associated with a bypassed purchase (e.g., failure to maintain a fashionable wardrobe), emulating members of an aspirational group (e.g., wearing designer brands worn by idolized celebrities), showing group affiliation (e.g., adapting an in-group's fashion sense), and celebrating special occasions through ritualized consumption (Hine, 2002; Pooler, 2003). Hedonic/recreational/leisure reasons for shopping related to adventure (for sensory and intellectual stimulation), socializing with friends and family, interacting with others, creating a sense of community, self-gratification (e.g., 'treating' oneself), information gathering (about trends, fashions, and products), finding 'perfect' gifts, self-definition (through trial-and-error, especially among Millennials), psychological gains from finding bargains (e.g., confirming intelligence and deal-finding ability), stress reduction, entertainment, prestige/conspicuous consumption, fantasy, and escapism (Arnold & Reynolds, 2003; Babin, Darden, & Griffin, 1994; Bäckström, 2011; Hirschman, 1983; H.-S. Kim, 2006; D. Lee & Hyman, 2008; Mano & Oliver, 1993; Scarpi, Pizza, & Visentin, 2014; Sherry, 1990).

Of course, with benefits came costs. Shopping, especially processes associated with product search and evoked set creation, is time intensive, mentally exhausting, and repetitive (Karimi, Papamichail, & Holland, 2015; Punj, 2012). On average, shoppers reported spending 1.63 hours each weekday and 1.87 hours daily on weekends and holiday to purchase goods and services (U.S. Bureau of Labor Statistics, 2017). Online shopping takes the average adult consumer five hours weekly, with Millennials and Gen Xers taking six hours, Baby Boomers taking four hours, and seniors taking 2.5 hours (V12 Data, 2017). In addition, shopping encourages materialism and other attitudes/behaviors contrary to human flourishing (i.e., true happiness) (Seligman, 2002). Consumers pursuing materialistic goals often focus excessively on acquiring goods and shopping is the venue for achieving such goals (Goldsmith, Flynn, & Clark, 2011).

Given increasingly hectic lifestyles, evermore pervasive preferences for vacating the hedonic treadmill, the relative attractiveness of many non-shopping-related activities, and rapid enhancements in AI-related technology, is the 'next big thing' a personal internet shopping agent (PISA) capable of supplanting most human shopping activity? How would such a PISA appear?

Personal Internet Shopping Agent (PISA) Framework

A 'bot' is a software application that runs automated tasks over the internet; in a retail context, it is called a 'shopping bot' (or [intelligent] shopping agent or [intelligent] recommendation agent). Initially, shopping bots were designed to help consumers make better choices and decisions when shopping online. At their heart, shopping bots would perform simple and repetitive tasks or relieve consumers from information overload (Aljukhadar, Senecal, & Daoust, 2012-13).

Predictions about future retailing include substantial changes in consumption behavior (Pantano & Timmermans, 2014) and increasingly prominent query-based AI systems (Grewal, Roggeveen, & Nordfält, 2017). In assisting consumers by facilitating product searches and purchase decisions, these systems approximate human intelligence. Initially, internet shopping bots/agents relied on crude information gathering, processing, and presentation. Currently, shopping engines rely on AI-powered subsystems that improve performance functionality and adaptivity to user needs and preferences.

The PISA framework presented here assumes a two-decade evolution from predominantly human-centric shopping augmented by internet-facilitated information search to predominantly autonomous, AI-powered personal shopping agents. That is, PISAs are 'next generation digital assistants' capable of replacing consumers' efforts to perform automatable rudimentary and repetitive shopping activities. Preliminary efforts by retailers such as Amazon (e.g., recurring orders, dash-buttons, and embedded recommendation engines) and Google (e.g., digital concierge) suggest increasingly automated purchasing processes meant to overhaul and simplify consumers' lives (Farah & Ramadan, 2017; Google, 2018).

Research on intelligent shopping agents has emerged from several disciplines: marketing/retailing, economics, business information systems, and computer science. Because researchers frequently adopt a silo approach, their efforts to understand intelligent agent functionality have focused on domain-specific rather than integrative inquiries. Marketing and retailing scholars have considered shopping agents from the consumer's/user's perspective; for example, they have studied agent interface design, users' satisfaction, users' cognitive effort, and gender differences (Doong & Wang, 2011; Verruck & Nique, 2017; Xu, Benbasat, & Cenfetelli, 2014). Their research suggests 'smart' recommendation agents (which focus on effort reduction) outperform 'knowledgeable' recommendation agents (which focus on seeking better product fit) for easing consumers' decision-making burden (Punj & Moore, 2007). In contrast, computer and decision scientists have considered shopping agents from a systems perspective: for example, they have studied objective performance (number of vendors, price dispersion, low/high price) and recommendation bias (Ma, Liao, & Lee, 2010; Xiao & Benbasat, 2018).

The Figure depicts a generic blueprint for PISAs. An independent PISA is comprised of four subsystems. To initiate PISA activity, a user requests a specific product offering through a GUI-based shopping agent console. Based on the request, a pre-processing filter—Subsystem #1—

fulfills the following functions: determine spidering pattern; fetch data; parse and identify useful data/information; and file information from online sources.

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Information passed to Subsystem #1 originates mainly in big data repositories and/or the internet. Some information, such as past shopping behavior or family buying history, may be stored in proprietary user-only accessible personal data sources (e.g., emails or invoices). Depending on the task, Subsystem #1 will seek information from sources that best match the consumer's goal(s) and the buying situation. For example, requests to repurchase OTC medicines will be treated differently than requests to repurchase light bulbs.

Subsystem #2 or the 'PISA engine' is the decision-making model manager that creates buying solutions with information passed from the pre-processing filter (i.e., Subsystem #1). This subsystem specifies and optimizes the decision-making model (H.-J. Kim, Kim, & Lee, 2009). First, it identifies decision goals (e.g., least expensive or highest quality) and factors in shopper-specified constraints (e.g., deliver in under two days). At this stage, consumers can provide qualitative information (e.g. preference for 'esthetic look') about the purchasing decision. The model can be optimized and solved for various endogenous and exogenous constraints, such as product availability, inventory levels, discount rates, consumers' ability to receive orders, and consumption conditions. Systems combining qualitative and quantitative inputs produce shopping solutions consumers favor (K. C. Lee & Kwon, 2008).

The engine is programmed to create a marketing offering matrix for comparison shopping. More sophisticated than bots, PISAs would incorporate sufficient AI to refine a consumer's initial decision parameters, conduct thorough product searches, and either suggest or order products matching that consumer's preferences. Most shopping bots already include algorithms that learn from consumers' previous queries. With further IT advances, shopping bots will evolve into PISAs, which will operate under a reinforcement learning principle: the engine is given a task to achieve and it learns by trial-and-error interactions with its environment (Yuan & Liu, 2000).

Subsystem #3 or the 'post-processing filter' is designed to limit full engine output to consumer-relevant information about available products. The PISA engine may generate buying solutions comprised of hundreds or even thousands of products when consumers seek multi-product solutions. For consumers, usefulness and the need for Subsystem #3 is only relevant if they choose to be involved (manual PISA mode) and the large volume of PISA-aggregated data compels engine-based organizing prior to human processing. In such cases, only a subset of solutions will be fed in Subsystem #4. In a fully automated and AI-controlled operation mode, the post-processing filter may not require activation.

Subsystem #4 is the visualization matrix/action module. Output from the post-processing filter is presented to consumers in the most accessible format for making purchase decisions. (Fortunately, information presentation format does affect how consumers make decisions when using recommendation engines (K.C. Lee & Kwon, 2008).) Alternatively, if consumers permit, then the PISA can act autonomously (i.e., complete purchases without consulting the consumer). Regardless, recommendation agents should align with consumer decision processes, which requires embedding AI as a tool for algorithm learning (Xiao & Benbasat, 2007).

The Table highlights possible levels of PISA control. At one extreme, users could fully control their PISA, thus limiting it to performing requested and monitored shopping tasks. At the other extreme, users could relegate inputs to an AI-enabled shopping console, thus allowing their PISA to make automated purchases. The latter extreme comes with many legal issues relating to contractual validity (i.e., capacity, consent, and liability for mistakes) (Bain, 2003). For example, who should bear the cost for an 'incorrect purchase' executed by a PISA? Hence, a suitable legal framework must precede full PISA implementation.

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Implications for Consumer Marketing

As envisioned, PISAs will be strictly software-based virtual entities developed by either an independent party, such as a programming group, or by a single- or multi-corporate-sponsor, such as Amazon (e.g., Alexa). Independent PISAs would be available for rent or purchase, whereas corporate-sponsored PISAs would be free because they would selectively present product offerings (e.g., a Wal-Mart PISA would focus predominantly on products sold by Wal-Mart). Consumers are likely to adopt recommendation agents they believe to be useful and controllable (Zhu, Chang, Luo, & Li, 2014).

Currently, there are three basic concerns for AI agents: incompleteness of information, oversimplification, and inability to mimic human behavior (Redmond, 2002). "In the age of Big Data, how do consumers view and assess the promise of personalization systems that may threaten to control or limit the information that they can access or share?" (Labrecque, Esche, Mathwick, Novak, & Hofacker, 2013, p. 266). This presents a moral issue rather than a 'limited information availability' issue. For example, should PISAs be permitted to scour the 'dark web' and purchase items that are, at best, semi-legal (Weisskopf, 2015)?

PISAs designed and trained to approximate a single consumer's behavior may be unable to account for new and untested products, gift-giving behavior, and/or impulse buying, among the many non-routine purchasing situations. In such cases, consumers may prefer to mitigate the AI engine's influence and instruct their PISA to perform a task for which it may not be fully trained. Obviously, avoiding oversimplification by inserting human agency into an otherwise automated purchase aid largely defeats the time- and effort-saving purpose of using PISAs.

From the consumer's psychological perspective, price is a unique and critical attribute that is not straightforward to model. For example, consumers are more price sensitive when focusing only on price, yet they exhibit less price sensitivity when focusing on quality-related attributes (Lynch & Ariely, 2000). If PISAs are programmed to avoid consumer biases, then they are not mimicking fault-prone human decision makers, which seems preferable but contrary to one of the aforementioned AI concerns.

Conclusions

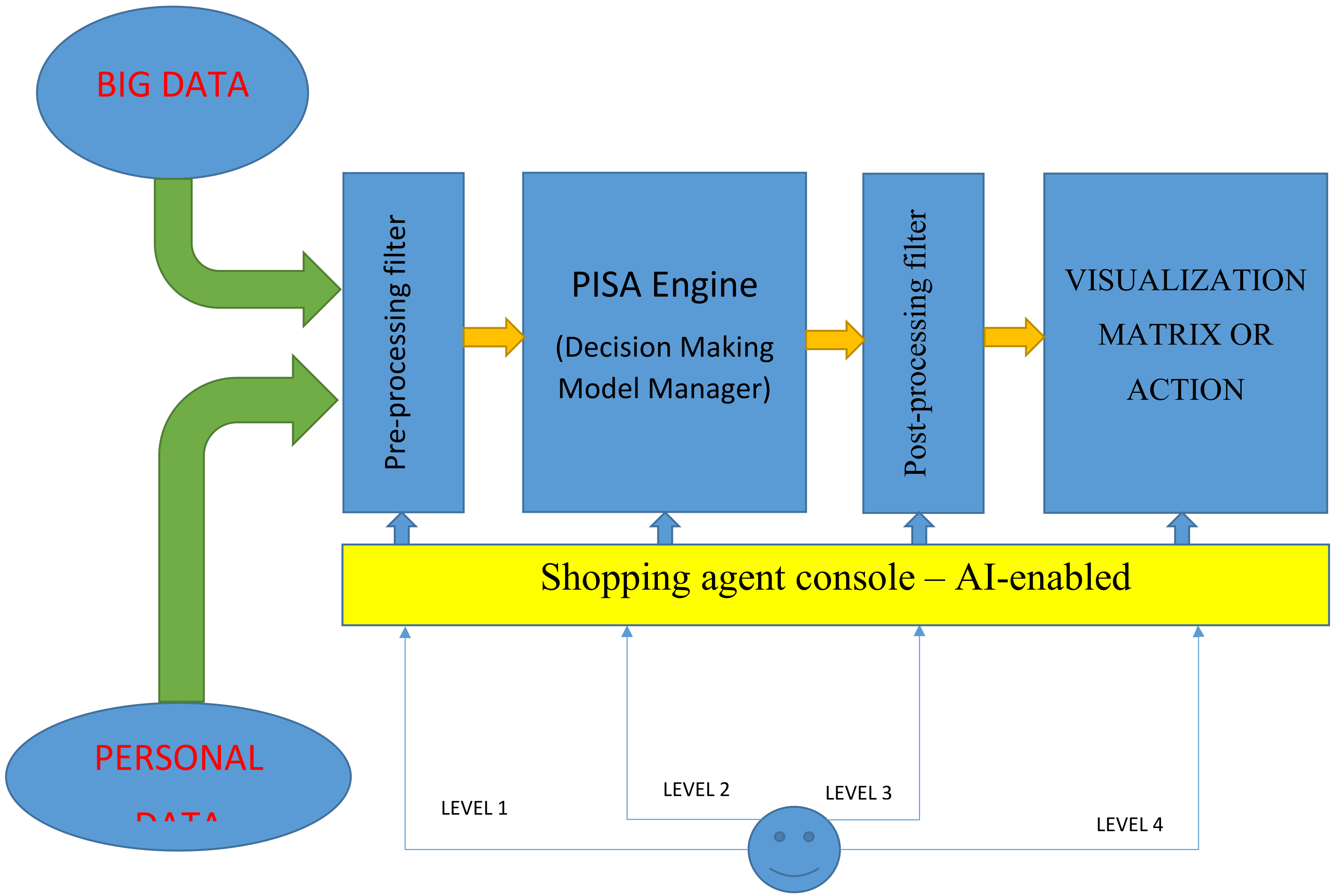
If exponential IT advances lead to a forecasted IT singularity within next 30-40 years (Kurzweil, 2005; Rifkin, 2014), then it is reasonable to estimate PISAs will be available in 10-15 years. As PISAs are inevitable, a debate about their eventual emergence is moot. Hence, marketing and retailing scholars should focus on how consumers and marketing practitioners will respond post-arrival to increasingly sophisticated PISAs. If nothing else, these scholars must safeguard consumers, as there is no guarantee competition, even among independently developed PISAs, will avoid many associated technical and societal problems.

Table 1. Levels of PISA Control (selected AI questions)

<u>Level 1 – User controlled</u>	Level 1 – AI controlled
What sources to search?	Decisions relegated to AI
What attributes to include?	
What is the search timeline?	
How much of past behavior to include?	
<u>Level 2 – User controlled</u>	Level 2 – AI controlled
What are important attributes?	
How many recommendations to generate?	Decisions relegated to AI
What information should be included/excluded in the process?	
<u>Level 3 – User controlled</u>	Level 3 – AI controlled
How many recommendations to present?	
What is the level of detail about each recommendation?	Decisions relegated to AI
Familiar or novel recommendations to display?	
<u>Level 4 – User controlled</u>	Level 4 – AI controlled

What should be the navigation and layout of the report?

Should the agent take action or ask for action approval? Decisions relegated to AI


BIG DATA
Pre-processing filter
PISA Engine
(Decision Making Model Manager)
Post-processing filter
VISUALIZATION MATRIX OR ACTION
Shopping agent console – AI-enabled
PERSONAL
LEVEL 1
LEVEL 2
LEVEL 3
LEVEL 4

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