Social Psychology Meets Social Computing: State of the Art and Future Directions

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ABSTRACT

Social computing platforms typically deal with data that are either related to humans or generated by humans. Consequently, effective design of these platforms needs to be cognizant of *social psychology theories*. In this tutorial, we review and summarize the research thus far into the paradigm of *psychology theory-informed design* of social computing platforms where the design is *guided* by theories from social psychology in addition to theories from computer science. Specifically, we review techniques and frameworks that embrace this paradigm in the arena of social influence. In addition, we suggest open problems and new research directions.

CCS CONCEPTS

• **Applied computing → Psychology**; • **Information systems → Collaborative and social computing systems and tools**;

KEYWORDS

Social psychology, online social influence, theory-informed design

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1 INTRODUCTION

Systematic and logical engagement of theories to inform design is foundational in designing technology for human use [29]. Theories can facilitate in making pragmatic choices in design. Indeed, many designs of social computing solutions are grounded in theories from computer science. Specifically, these solutions deal with data that are either related to humans or produced by humans. Consequently, they need to be cognizant of the influence of behaviours of (interacting) individuals. This has led to a flurry of research since the last decade on *psychology theory-informed design* of social computing frameworks where theories from social psychology[1], in addition to the theories from computer science, are *explicitly* utilized to guide their design. For example, social psychology theories such as *conformity* and *confirmation bias* have been exploited to guide the design of several online social influence analysis techniques [17, 19, 20, 22, 24, 34].

Table 1: Tutorial overview.

Topic	*Representative papers*
Introduction	-
The concept of psychology theory-informed design	-
Relevant social psychology theories	[1, 2, 6, 8, 28, 33, 35]
Psychology theory-informed diffusion models	[20, 22–24, 26]
Psychology theory-informed online social influence	[17–20, 22, 34, 37]
Future research direction	-

This tutorial gives a comprehensive introduction to the topic of *psychology theory-informed design* of online social computing techniques and frameworks. A hallmark of this tutorial is to emphasize research that aims to bridge traditionally orthogonal fields, namely, social computing and psychology. Specifically, we review techniques and frameworks in the arena of social influence that *explicitly* utilize social psychology theories in their design. We focus on this topic as a significant number of psychology theory-informed designs in the literature have focused on it. A brief overview of the scope of the tutorial is as follows.

- **Psychology theory-informed design:** We begin by introducing the notion of *psychology theory-informed design* where the design of social computing frameworks exploits social psychology theories. To this end, we introduce relevant theories from psychology (*i.e.,* theories on conformity [3], confirmation bias [28], attenuation [35], and interference [6]) that have been explicitly used to guide the design.
- **Psychology theory-informed social influence analysis:** We review social psychology theory-informed design of online social influence analysis. Specifically, we focus on the information diffusion models and social influence estimation techniques that are grounded on the above theories.
- **Future research directions:** Finally, we discuss intriguing open problems in psychology theory-informed design of social computing frameworks. We discuss how this paradigm paves the way for rethinking a broader set of social computing problems, explore new psychology theories that

[1] Social psychology is the study of how individual or group behaviour is influenced by the presence and behaviour of others [1].

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Figure 1: Psychology theory-informed design of social computing frameworks.

may influence these problems, and data-driven quantitative modeling of psychological elements that influence solutions to the social computing problems.

Table 1 shows the topics and representative works covered by the tutorial. A short teaser video is available at https://youtu.be/kuR1W02jdxQ.

2 TUTORIAL OUTLINE

Our presentation follows a top-down approach, starting from the notion of *psychology theory-informed design*, to relevant theories of social psychology that influence the design of existing social influence analysis techniques, proceeding to the review of various social psychology theory-informed design of these techniques, and concluding with future research directions in this arena.

2.1 Psychology Theory-Informed Design

The usage of theories to inform design is fundamental to designing technology for human use [29]. Oulasvirta and Hornbaek [29] claim for a theory to be called a "theory for design", it must take design forward and reach *good* features. However, only exploiting theories from computer science to guide the design of solutions for social computing problems is often inadequate. Social data is typically related to humans or produced by humans. It is also mostly consumed by humans. Hence, social computing solutions that incorporate theories from psychology in their design process in a systematic and logical way are likely to steer toward solutions that yield desirable outcomes to end-users. We refer to this design process as *psychology theory-informed design*. Figure 1 depicts the notion of such a design process where the design of a social computing framework is *explicitly* informed by psychological theories. In this tutorial, we review research efforts that instantiate such a framework in the context of social influence analysis. We focus on the *relevant* social psychology theories as these are most germane to individuals or a group of interacting individuals. In the sequel, we shall introduce these theories and review research on psychology theory-informed design focusing on online social influence.

2.2 Social Psychology Theories

There are many theories in social psychology. We briefly introduce a subset of these. Specifically, we focus on those theories that have been *explicitly* utilized in existing psychology theory-informed designs for online social influence.

Conformity Theory [3]. There is a long stream of work in social psychology [1–4] that has shown the existence and importance of *conformity* in social interactions. Intuitively, it refers to the inclination to align our attitudes and behaviours with those around us. Conformity can be broadly classified into two types, namely *informational conformity* and *normative conformity* [8]. The former occurs when people conform to peer views in an attempt to reach appropriate behaviours and attitudes due to lack of relevant knowledge. The latter occurs because of the desire to be accepted or that keep us from being isolated or rejected by others.

Confirmation Bias Theory [28]. In social psychology, the *confirmation bias* theory states that individuals have the tendency to seek out information (search for, interpret, favour, recall) that supports their prior or existing beliefs or values, often at the expense of ignoring inconsistent information. This is thought to be done unconsciously or unintentionally; thus the bias. It does not mean that individuals are incapable of providing perspectives that counter their own beliefs, rather that they are not motivated to do so. In this scenario, the evidence selection to support prior or existing beliefs or values is usually one-sided, either disregarding the evidence supporting the opposite views or underweight the evidence of alternative views. Biased individuals would also tend to behave less receptively to the alternative views presented to them.

Attenuation Theory [35]. This theory aims to explain the tendency of individuals to process only certain parts of their world while ignoring others. It posits that even when attention of an individual is directed elsewhere, unattended messages are attenuated (*i.e.,* weakly processed information) but not entirely blocked from further processing and entry into memory. In particular, weakly processed information has different thresholds of recognition depending on its relevance and significance to the individual.

Interference Theory [6]. The interference theory-based forgetting posits that all forgetting of humans cannot simply be explained by the time-related decay of memories. It can be classified as *retroactive* or *proactive*. The former type of interference occurs when new information impedes the ability to retrieve previously acquired memory traces whereas the latter refers to the case of previously acquired memory traces interfere with the ability to retrieve new information. Research shows that retroactive interference is primarily responsible for forgetting in daily life.

2.3 Psychology Theory-Informed Diffusion Models

Online information diffusion and social influence rely on the "word-of-mouth effect" between individuals, which is influenced by psychological elements of humans. Consequently, there has been plenty of research in social psychology to investigate these elements [1]. Among the many social psychological elements, conformity, confirmation bias, interference, and attenuation theories have been leveraged to build online social influence analysis frameworks.

Diffusion models and conformity theory. Information diffusion models study the hidden mechanism on how information spreads in a target social network [11]. Since conformity often plays an important role in how a group of interacting individuals respond socially, it naturally influences the information diffusion/spread process.

Li *et al.* [20] presented a novel framework called CHASSIS which integrates the interplay of informational and normative conformity into Hawkes process-based information diffusion model. Specifically, they detect and quantify conformity by analysing the *diffusion trees* and propose an efficient semi-parametric inference algorithm, wherein the parametric evaluation procedure assists in identifying conformity of individuals, and the nonparametric procedure learns the triggering kernel functions flexibly in a data-driven way without the need of prior domain knowledge.

Diffusion models and attention attenuation and interference theories. Luo *et al.* [23] observed that after individuals acquire information at a given time point, new information will be generated with time which interferes with the previous information. As a result the intensity of the previous information will decay. People also tend to pay less attention to the previous information with the emergence of new information. To capture this behaviour of individuals, they propose an information dissemination model called the *resistant linear threshold* (RLT), which is an extension of the classical linear threshold model [11], to embrace attenuation and interference theories. Specifically, resistance indicates that attention and interest of individuals to previous information decline and the *activation threshold* parameter is used to represent it.

Diffusion models and confirmation bias. Most of the existing information spread and opinion dynamic models are oblivious to confirmation bias in their design [24]. Confirmation bias catalyses the creation of "echo chambers" within social networks, which facilitates spread of misinformation and polarization [14]. Recently, Mah *et al.* [24, 26] proposed a *confirmation bias-informed* information spread model over a social network with two competitive information sources. Specifically, it is built on the opinion dynamics model in [25] and exploits a piecewise linear confirmation bias model. The information spread problem is formulated as a zero-sum game and investigates the pure Nash equilibrium point and the impact of confirmation bias on it.

2.4 Psychology Theory-Informed Influence Estimation & Maximization

We review social influence estimation and maximization techniques whose designs are informed by theories from psychology. These techniques typically exploit existing information diffusion models.

Social influence estimation and conformity theory. Traditional online social influence estimation techniques fail to consider conformity in their design [21]. In particular, the *propagation probability* from u to v typically captures how it can be affected by the influence of u but not conformity of v. Since the last decade, this has led to increasing research efforts on *conformity-informed* design of online social network analytics techniques. The seminal work of Li *et al.* [17] studied the interplay between influence and conformity by exploiting the positive and negative relationships between individuals. Tang *et al.* [34] introduced a probabilistic factor graph model for predicting user behaviour which is informed by the conformity of users. The work in [37] assigns hidden roles to users prior to learning the correlation between roles and conformity.

Influence maximization and conformity theory. Li *et al.* [18, 19] modeled conformity in the context of the influence maximization (IM) problem [16, 21]. They proposed a *conformity-aware cascade* (C^2) model, which exploits the interplay between influence and conformity in computing the propagation probabilities of nodes for estimating influence spreads. They presented a solution towards the IM problem under C^2. This effort is extended in [19] by considering *context-specific* influence (*e.g.,* topics) and conformity of nodes.

The study in [22] further classifies conformity into *friend* and *group* conformity. The former refers to one's inclination to conform to her friends' whereas the latter refers to one's inclination to behave in the same way to the group she belongs to. It advocates that the friend conformity can be attributed to the similarity between a pair of friends' *profiles*, while the group conformity of a node u can be defined as the similarity between the profile of u and that of the group u belongs to. Based on the two conformity behaviours, an information diffusion model is proposed where the probability of u influencing v is the product of their friend conformity and the group conformity of u. Based on this model, a *group-based* IM problem to select k seeds to maximize the influence spread under the conformity-aware diffusion model is presented.

2.5 Future Directions

Research on the psychology theory-informed design of social computing techniques is still in its infancy and there are many opportunities for future research. The last part of the tutorial presents a non-exhaustive list of open problems in this inter-disciplinary area.

Expansion to larger social analytics problem sets. It is easy to envisage that the aforementioned social psychology theories may trigger rethinking of many existing solutions to social computing problems. For instance, searching social networks (*e.g.,* community detection and search) has received increasing attention. Although psychological elements (*e.g.,* conformity, confirmation bias) of interacting individuals play important roles in community formation, existing techniques are typically psychology-oblivious [9].

Bias and fairness in data-centric computing frameworks have recently gained increasing attention [27, 31, 32]. These efforts primarily focus on (a) the detection or quantification of bias and fairness using a variety of metrics and (b) techniques for bias mitigation (*i.e.,* debiasing). Designs of these metrics and techniques typically do not explicitly embrace theories from psychology.

Theories from psychology also have a role to play in guiding the design of data quality techniques to understand the quality of the data and the trust that should be given to them. For example, controversy detection techniques [5] in collaboratively-edited content such as *Wikipedia* are psychology-oblivious. Intuitively, in such an environment confirmation bias and conformity are at play and hence the modeling of collaborative data needs to be psychology-informed for superior understanding of data quality. Similarly, techniques for understanding fake news propagation can benefit from social psychology theories [15, 38].

Expansion of psychological theories in social computing. The above issue highlights the role aforementioned social psychology theories can play in the design of solutions of a broader set of social computing problems. These theories are just the tip of the iceberg. There are many relevant theories from psychology that are yet to be considered in our psychology theory-informed design. For instance, *social impact theory* [1] has a role to play in understanding social influence. This theory posits that the amount of influence a person experiences in group settings is influenced by (a) strength (power or social status) of the group; (b) immediacy (physical or psychological distance); (c) number of people in the group exerting the influence. Similarly, *role theory* [1], where roles that people occupy provide contexts that shape behaviour, has the potential to contribute to information propagation techniques among others. Furthermore, note that social data often is consumed by humans (Figure 1). Although this data can be voluminous, cognitive psychology[2]-aware solutions (*e.g.,* cognitive load theory [33], interference theory) to generate, visualize, and explore social data and results are still underexplored in the literature. Hence, a natural extension is to explore these theories in the holistic design of social computing techniques.

Data-driven quantitative models of psychological elements. Although there are quantitative models for some psychological theories (*e.g.,* confirmation bias [24, 28]), many do not benefit from such models. Hence, existence of massive human-related data opens up the opportunity to build data-driven quantitative models for various psychological elements. To this end, the efforts in [20] have taken the initial step to build a quantitative model for conformity. We believe that there are significant opportunities for data-driven techniques to influence social psychology.

3 BIOGRAPHIES

Sourav S. Bhowmick is an Associate Professor at NTU, Singapore. His research expertise is in data management, human-data interaction, and data analytics. He is co-recipient of Best Paper Awards in ACM CIKM 2004, ACM BCB 2011, VLDB 2021, and ER 2023. He is also co-recipient of the 2021 ACM SIGMOD Research Highlights Award. Sourav is serving as a member of the SIGMOD Executive Committee, a regular member of the PVLDB advisory board, and a trustee of the VLDB Endowment. He was inducted into Distinguished Members of the ACM in 2020.

Hui Li is a Professor at the Xidian University, China. His research interests includes social computing, knowledge discovery, graph mining, and data privacy. His research has appeared in premium venues such as ACM SIGMOD, VLDB, SIGKDD, and the VLDB Journal. His work on competitive influence maximization was nominated for the best paper award in SIGMOD 2015.

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Yining Zhao is a doctoral student at NTU. Her research focuses on the psychology theory-informed design of social computing techniques. She received her Bachelor's degree in Computer Science in 2022 from the Sichuan University, China.

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