From WOM to aWOM – the evolution of unpaid influence: a perspective article

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Abstract

Purpose–Advances in artificial intelligence (AI) natural language processing may see the emergence ofalgorithmic word of mouth (aWOM), content created and shared by automated tools. As AI tools improve,aWOM will increase in volume and sophistication, displacing eWOM as an influence on customerdecision-making. The purpose of this paper is to provide an overview of the socio technological trendsthat have encouraged the evolution of informal infulence strategies from WOM to aWOM.

Design/methodology/approach–This paper examines the origins and path of development ofinfluential customer communications from word of mouth (WOM) to electronic word of mouth (eWOM) andthe emerging trend of aWOM. The growth of aWOM is theorized as a result of new developments in AInatural language processing tools along with autonomous distribution systems in the form of softwarerobots and virtual assistants.

Findings–aWOM may become a dominant source of information for tourists, as it can supportmultimodal delivery of useful contextual information. Individuals, organizations and social mediaplatforms will have to ensure that aWOM is developed and deployed responsibly and ethically.

Practical implications–aWOM may emerge as the dominant source of information for tourist decision-making, displacing WOM or eWOM. aWOM may also impact online opinion leaders, as they may bechallenged by algorithmically generated content. aWOM tools may also generate content using sensorson personal devices, creating privacy and information security concerns if users did not give permissionfor such activities.

Originality/value–This paper is the first to theorize the emergence of aWOM as autonomous AIcommunication within the framework of unpaid influence or WOM. As customer engagement willincreasingly occur in algorithmic environments that comprise person–machine interactions, aWOM willinfluence future tourism research and practice.

Introduction

Interpersonal communication between tourists about destinations and activities is a valuable customer decisionmaking tool which has evolved from direct, Word of Mouth (WOM) to incorporate mediated, Electronic Word of Mouth (eWOM) (Williams, Inversini, Ferdinand and Buhalis, 2017). The recent development of Artificial Intelligence (AI) algorithms that can autonomously create and distribute language outputs provides the future possibility of Algorithmic Word of Mouth, or communications created and shared by non-human AI tools that can support customer decision making about destinations and activities.

Past Perspective: From WOM to eWOM

Word-of-mouth (WOM) is defined as interpersonal communications aimed at influencing purchase behaviour, shared and created by unpaid individuals (Glynn Mangold, Miller and Brockway, 1999). Early observations in the 1950's identified the networked nature of interpersonal WOM along with its impact on the adoption of consumer products (Whyte, 1954). Slightly later work verified the ability of WOM to reduce the uncertainty around product purchases (Arndt, 1967) and incorporated discussions made via a medium rather than face to face (Westbrook, 1987).

Tourism WOM researchers have examined the content, source characteristics and outcomes of WOM (Confente, 2015). WOM shared by trusted opinion leaders can be particularly influential as they may share the demographic or professional characteristics of the potential visitor (Jamrozy, Backman and Backman,1996). At the destination level, positive WOM can enhance destination image and increase awareness (Phillips, Wolfe, Hodur and Leistritz, 2013). For organisations, positive WOM can enhance their reputation, increasing revenues and reducing the cost of promotion.

Technological developments in communication have seen the emergence of tourism eWOM (Electronic Word of Mouth) or unpaid communication by online users (Ismagilova, Dwivedi, and Slade,2019). eWOM is visible to a wider range of direct or indirect customers as it may be hosted in public settings (Erickson and Kellogg, 2000). eWOM can shape decisionmaking by tourists and takes multiple formats (reviews, recommendations, social media postings and blogs), modes (one to one and many to many) and timing (synchronous and asynchronous) (Chen and Law, 2016). Researchers have identified multiple motivations for sharing eWOM that range from self-interest to altruism which may influence the type, location, valence (positive) and type of eWOM posted (Bronner and De Hoog, 2011). In addition to internal motivation, users sharing eWOM also receive validation via visible reputation systems (Ziegler and Golbeck, 2007). eWOM is not always intentional, and actions such as liking a Facebook page may provide social endorsement for friends and followers (Erkan and Evans, 2016). eWOM recipients attempt to evaluate veracity by examining the content, source and online interaction behaviour of posters (Filieri, 2016). Platforms which distribute eWOM may act as a mediator or intermediary of Organization/Customer relationships, influencing the nature of interactions (Leung, Sun and Bai, 2019). In addition to content and distributor characteristics, recipients may examine the tone and valence (positive, negative or balanced) of eWOM.

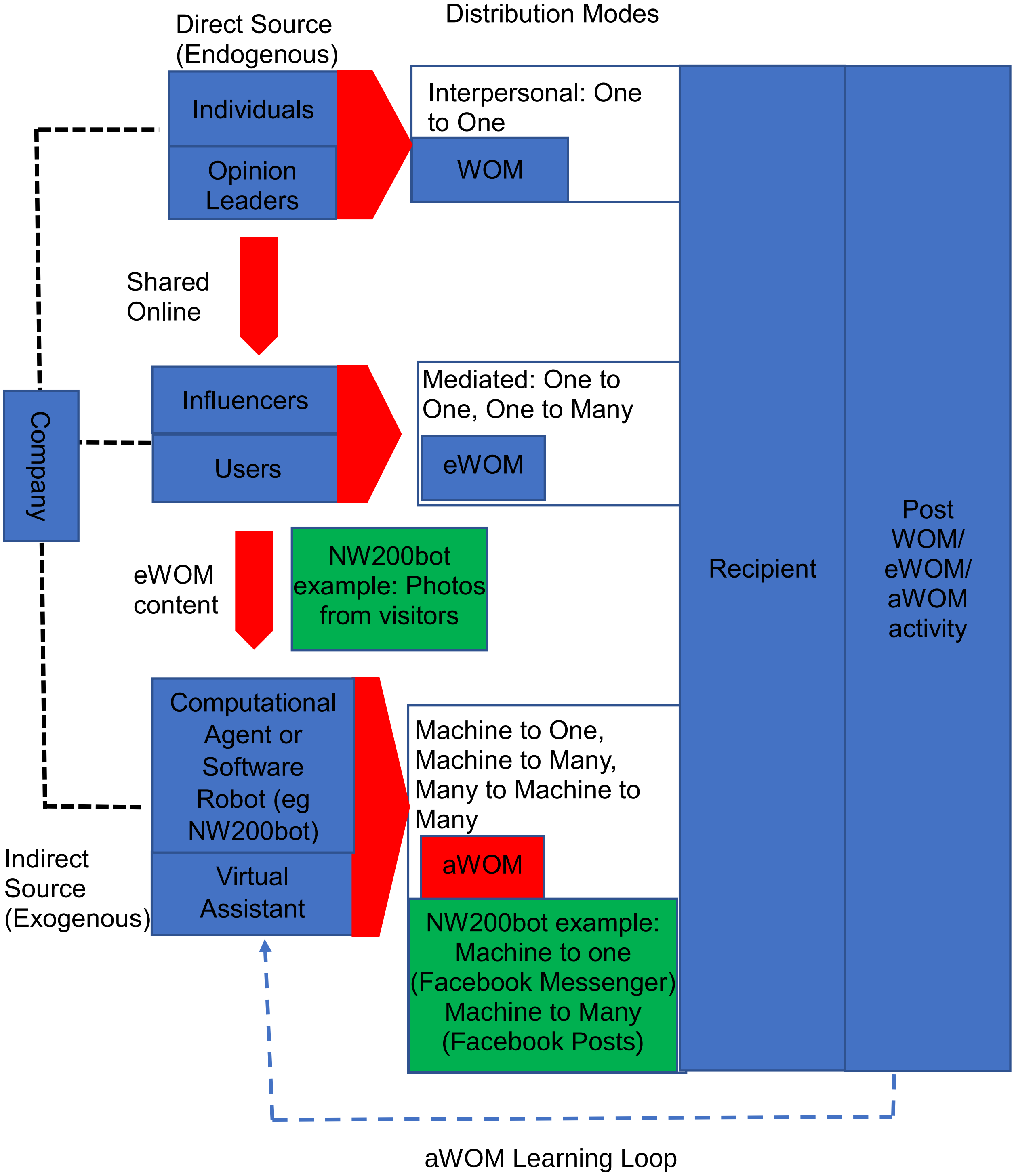
Unlike WOM, eWOM distribution can be automated, allowing opinion leaders to engage with larger groups of potential tourists (Orhean, Pop, and Raicu, 2018). Directly, endogenous eWOM has been found to influence perceptions, purchases and loyalty with direct financial outcomes to organisations (Viglia, Minazzi, and Buhalis, 2016). Indirectly, eWOM can also exert social influence, shaping customer information search and evaluation processes. The success of the latter encourages the creation of exogenous eWOM that exploits network connections among customers (López, Sicilia and Hidalgo-Alcázar, 2016). This type of eWOM relies on the distribution of company information by employees, customers and paid opinion leaders, enabling a formal promotional strategy to appear as informal, endogenous eWOM. These tactics are difficult to detect and may also be deployed by organisations to attack competitors (Litvin, Goldsmith and Pan, 2008). Combined with the scale of social media platforms and automated distribution, negative exogenous eWOM can cause significant reputational harm to organisations or destinations.

Future Perspective: From eWOM to aWOM

Neural network Machine Learning algorithms trained on large volumes of data have supported the creation of Artificial Intelligence (AI) systems that can perform autonomous detection and evaluation of patterns in written text or audio (Ghahramani, 2015). They can be used to summarise text eWOM (Young, Hazarika, Poria and Cambria 2018), to create text outputs from non-human sources such as sensors that exhibit the format, content and valence of credible eWOM (Tikhonov and Yamshchikov, 2018). AI-generated content is distributed via virtual assistant platforms such as Alexa (Amazon) and software robots (chatbots) (Bustard, Bolan, Devine and Hutchinson, 2019). In addition to content, AI tools can evaluate interactions with outputs to autonomously evaluate customer engagement with content and plan future outputs.

In tourism, these summaries of existing eWOM and machine-generated text may be used to support decisionmaking about destinations or services. In these applications, they can be classified as Algorithmic Word of Mouth or aWOM(Figure 1). aWOM differs from eWOM as the content is created and distributed algorithmically from non-human sources, previous media or eWOM. When shared by AI assistants on mobile devices, aWOM can incorporate additional contextual information from the users' previous interactions such as travel patterns, sensor data from personal devices and friend/follower relationships that can personalise content to a greater degree than eWOM. For example, based on a user location a software robot could monitor use sensors and eWOM reviews to generate a text or voice post that describes the extent to which nearby attractions are crowded. This post is then shared via a software robot or virtual assistant. Another example is the NW200 bot (https://www.facebook.com/northwest200/), which aggregated and shared eWOM from Event attendees and autonomously shared race results from the event to interested subscribers. Unlike, eWOM, aWOM shared via personal assistants can examine subsequent recipient behaviour in order to improve content and distribution effectiveness.

Figure 1: Characteristics and modes of communications.



Conclusions and Future Research

As the capabilities of AI language processing continue to increase, aWOM may emerge as the dominant source of information for tourist decisionmaking. Customers increasingly expect real-time responses to emergent scenarios, encouraging the substitution of manually generated responses for aWOM (Buhalis and Sinarta, 2019). It is not yet known how aWOM may shape the patterns, habits and activities of tourists established from the usage of WOM or eWOM. Future research could examine the extent and the contexts in which aWOM may substitute for WOM or eWOM. Research can also examine the impact of aWOM on online opinion leaders as they may be challenged by algorithmically generated content. aWOM tools may also generate content using sensors on personal devices, creating privacy and information security concerns if users did not give permission for such activities.

Exogenous aWOM may be used to deceive users by delivering company promotional materials in formats that mimic popular influencers along with interactions from programmed accounts to convince potential customers. Recent research has highlighted how algorithmically generated content and interactions have been used for political campaigning (Howard, Woolley and Calo, 2018) and aWOM may be used to attack competitors or depress demand for destinations. Social media and other online public platforms may be required to develop new identity verification systems to ensure that users do not engage in such deceptive practices.

In addition to decisionmaking, organisations and customers may co-create new services in order to respond to new, algorithmic barriers that monitor user identity, content type and distribution approaches (Buhalis, Harwood, Bogicevic, Viglia, Beldona and Hofacker, 2019). Future research can examine the evolution of customer engagement in these new algorithmic environments that comprise of person-machine interactions.

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