What Supports Serendipity on Twitter? Online Survey on the Role of Technology Characteristics and Their Use

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ABSTRACT

Serendipity experiences are highly desirable in work life, considering both individuals' learning and organizational innovation capacity. This study looks into information and social serendipity in the context of Twitter. While Twitter can be viewed as a fruitful platform for serendipity to emerge, there is little understanding of what technology characteristics and use practices contribute to such experiences in work-related use. Drawing from the functional affordances theory, the paper investigates the role of presenteeism, self-disclosure, recommendation quality and pace of change, and different types of Twitter use as possible antecedents of serendipity. A cross-sectional international online survey was conducted with 473 respondents who actively use Twitter in their work. An exploratory factor analysis was performed, followed by linear regression analysis to identify relevant statistical associations. The findings indicate that presenteeism (i.e., the fundamental element of reachability) seems to have an effect on serendipity while the more designable characteristics, like the quality of recommendations, do not. Overall, the findings imply that serendipity experiences are primarily explained by individual characteristics like personality and specific ways of using Twitter. This is amongst the first studies on the role of Twitter characteristics as functional affordances in the formation of serendipity. The extensive empirical study contributes a detailed analysis of the antecedents of serendipity and opens avenues for research and design to identify new serendipity-inducing mechanisms.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Information systems → Social networks**; *Internet communications tools*; *Web searching and information discovery*.

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KEYWORDS

Information serendipity, Social serendipity, Serendipitous Social Encounters, IT-supported Serendipity, Social networking, User experience, Knowledge work, Online survey

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1 INTRODUCTION

Social media services are actively utilized in work life as they open access to vast networks of relevant knowledge and experts and enable the exchange of ideas and expertise [71]. Organizational studies demonstrated that employees strategically use micro-blogging services like Twitter to increase their visibility and influence through the expression and promotion of professional identities [73]. Prior research suggests that Twitter supports the discovery of unexpected yet valuable content and contacts for professional interests [56], which implies that Twitter use offers a relevant empirical context to study experiences of serendipity.

Serendipity is conceptualized as an unsought yet fortunate experience prompted by an individual's interaction with ideas, information, objects, or phenomena [47]. Prior research on serendipity seems to largely focus on its role in information retrieval [2, 6], its importance in creativity and innovation [3, 32], and in knowledge building and learning [9, 55]. In recent literature, serendipity has been recognized as a strongly positive experience worth pursuing [16, 37], especially in professional activities [52, 57]. Since this study focuses on serendipity within the context of Twitter use, we cover both *information* and *social* serendipity.

However, little is known about if and how the technology characteristics and especially designable service features might support serendipity experiences or if certain usage practices tend to lead to such. Despite its desirability as a specific user experience, designing for serendipity will remain an elusive goal if the contributing mechanisms are unclear. Since chance and happenstance are central elements of serendipity, the possible factors contributing to it are likely diverse. Prior work features only a few attempts to reveal the antecedents of IT-supported serendipity, primarily in the context of information retrieval [39, 46], with little attention to its social counterpart. Therefore, by investigating a range of factors, the present study extends the understanding of the IT characteristics that serve as antecedents of information serendipity or social serendipity on the most popular microblogging service Twitter. We considered Twitter a fruitful context for researching serendipity as it is commonly and strategically used for professional purposes, and serendipity is an important element in its user experience [59, 73].

Thus, this exploratory research focuses on the following questions: **RQ1.** *What technological characteristics contribute to the experiences of information and social serendipity on Twitter?* **RQ2.** *How do these characteristics associate with the types of Twitter use?* We conducted a cross-sectional online survey of 473 respondents who use Twitter in their work. Drawing from the functional affordances theory [25, 48], we analyzed the effects of perceived *recommendation quality* [54], *pace of change* [5], *self-disclosure* [76] and *presenteeism* [5], and their relations to experiences of serendipity. Additionally, we included background and personality characteristics as control variables to understand the overall proportion of service features in explaining serendipity.

The quantitative analysis demonstrates that the examined technology characteristics provide limited direct support for serendipity. Nonetheless, all the investigated characteristics appear to be significantly associated with different types of Twitter use. The findings also illustrate that users who consume content by following active discussions and exploring others' tweets experienced higher levels of information serendipity than users who were actively producing content. Additionally, personality characteristics, such as *openness to experience*, *neuroticism*, and *conscientiousness*, were found to be essential in serendipity.

The primary contribution of the article is the report of an extensive quantitative study on how various technology characteristics and types of Twitter use can support the emergence of information and social serendipity in the context of professional life. The results provide insights into technology's role in shaping serendipity. In contrast to prior research, which focuses on serendipitous encounters related to information discovery, we extend the understanding of the little-studied concept of social serendipity. Furthermore, we anticipate the study to encourage the exploration of new serendipity-inducing mechanisms on social media services utilized for professional purposes.

2 RELATED WORK

Many research fields studied serendipity, resulting in numerous conceptualizations 1. For instance, in organization studies, the concept is treated as a behavioral and social pattern worth pursuing due to the positive effects on knowledge work and collaboration [30, 59]. In computer science, the concept is relevant, especially in information retrieval (IR) and Recommender Systems (RecSys) research, where it is regarded as a measure for preventing algorithmic bias and enabling information diversity [36, 60].

Research in Human-Computer Interaction (HCI) and Computer-Supported Cooperative Work (CSCW) has explored two branches of the phenomenon: natural serendipity, which is unplanned and non-deterministic, and IT-supported serendipity—facilitated or triggered by technology. Studies of natural serendipity cover, for instance, exploratory studies on social awareness and impromptu encounters within work environments [34]. Research on IT-supported serendipity has focused on designing and evaluating IT artifacts that aim to facilitate chance encounters between co-workers or collocated individuals [58] and recommender systems for surprising content discoveries [1].

Search engines present a classic example of IT-supported serendipity by opening access to enormous content and different pathways to encounter it. Notably, Twitter and other services with user-generated content differ from traditional information search engines by exposing users to content that is not deliberately searched for. Additionally, since Twitter is used to support diverse tasks, it is found to make discoveries unpredictable [68]. Such multi-purpose use of the platform promotes one of the key qualities of serendipity—the revelation of unsought connections [20]. On Twitter, serendipity can emerge due to the dynamics of personal social networks and user-generated content, which are enabled via 'follow,' 'mention,' 'favorite,' and 'retweet' features [62].

For this study, it is relevant to establish a conceptual separation between two target branches of serendipity—information and social serendipity. Information serendipity refers to unexpected yet fortunate discoveries of information and manifests in stumbling upon useful content (e.g., tweets, links, and hashtags). Social serendipity refers to unexpected encounters with other people (e.g., followees and followers), resulting in personal or professional benefits. The following sections will further conceptualize these two facets of serendipity.

2.1 Information Serendipity

Prior research on information serendipity has discussed whether it is possible to design for serendipity at all. After all, technology features tailored to satisfy and predict users' desires might decrease the element of surprise [39, 42]. While engineering serendipity with technology is considered an oxymoron, researchers concluded that it is possible to enable experiences that can be subjectively perceived as serendipitous [4, 41]. For instance, Makri et al. [42] proposed design strategies such as facilitating the revelation of patterns, seizing opportunities, relaxing personal boundaries, and supporting making a connection with previous experiences.

The perception of serendipity depends on various factors, which can prevent or establish the context for serendipitous encounters, for instance, trust and privacy [39]. By studying accidental discoveries on Twitter, McCay-Peet and Quan-Haase [46] also revealed the key factors influencing the perception of serendipity like user's age and activity level. The older the user and the more active she is on the platform, the higher the probability of fortunate information discovery and the strength of the perception of serendipity.

Design-oriented research in this domain has produced various artifacts, mainly content recommender systems, that support surprising discoveries. For instance, Toms and McCay-Peet (2009) designed and evaluated "a serendipity inducing tool" that enables unexpected suggestions from Wikipedia readings. Campos and Figueiredo [12] implemented a web search system, 'Max,' that allows divergent exploration of potentially useful Internet resources. Such systems typically utilize a similarity-based recommendation approach that relies on a history of users' inputs. More unexpected information

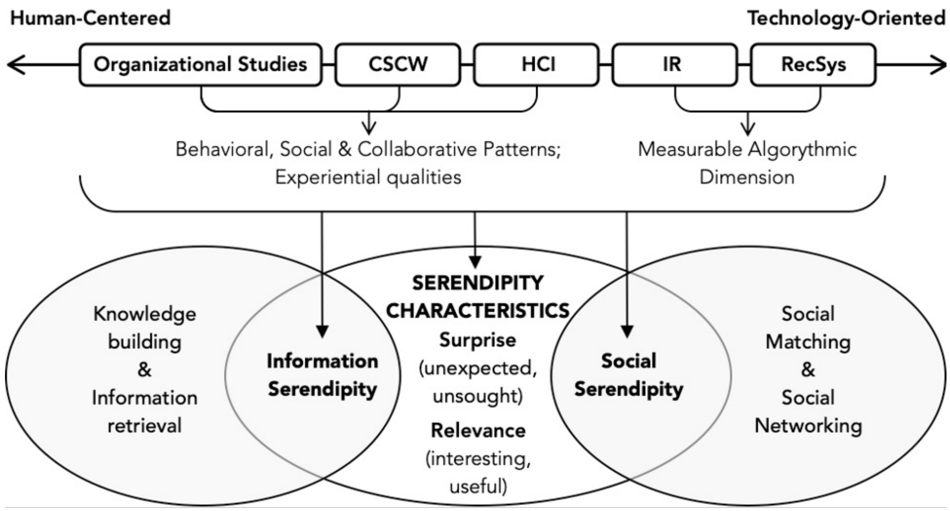

Figure 1: Overview of the serendipity conceptualization in different scientific fields, key characteristics of the serendipity, and the difference between information and social serendipity.

is provided in interactive library visualizations that support the opportunistic exploration of books [70]. Such services provide a more random and diverse pool of content selection, yet the chances of getting relevant suggestions are decreased.

2.2 Social Serendipity

While serendipity has been primarily studied within the context of information retrieval, little attention is paid to its social counterpart, that is, unexpected yet beneficial encounters with relevant people. In HCI and CSCW research, social serendipity is rarely addressed explicitly, even though related topics have been investigated. For instance, there are exploratory studies on daily spontaneous encounters [34], chance encounters [31], and social awareness [75] in collocated work environments [58]. A recent survey study highlights that not all chance encounters result in serendipitous experiences and suggests that technology might play a minor role in the process of social serendipity [57].

Design-oriented studies have investigated the means to enable chance encounters (or impromptu encounters), aiming to enhance awareness and interactions between collocated or distributed workers. For instance, Erickson and Kellogg [22] introduced the concept of 'socially translucent systems,' which increases the visibility of employees' activities in the context of large groups and organizations. Jeffrey and McGrath [31] designed a collaborative working environment for informal online interactions to help employees to make new connections and share knowledge. Eagle and Pentland [21] built a socially curious mobile service, which senses the contextual surroundings and encourages face-to-face interactions within a proximity range. Interestingly, such solutions are typically based on maximizing similarity in the social matching process, which might lead to anticipated rather than serendipitous encounters.

In summary, prior research agrees that technology artifacts could provide favorable conditions for serendipity. However, the question of how information systems could facilitate serendipity experiences remains unanswered. In contrast to the preceding research, we seek to understand the characteristics that facilitate both information and social serendipity in the professional use of Twitter. To understand the role of technology in the overall scheme of possible factors, we also investigate types of Twitter use, followership statistics, and personal background characteristics.

2.3 Serendipity and Professional Use of Twitter

Recent research on the work-related use of Twitter has established that serendipity experiences are critical for Twitter users and vital for organizational innovation practices [43, 59]. In a professional context, serendipity occurring in social media was found to foster the creation and use of new ideas [30, 73] and positively influence employees' performance [13, 59].

As Twitter allows vocationally motivated interactions between various individuals, communities, companies, and markets [50, 69], previous work has identified different professional purposes for using Twitter. For example, van Zoonen et al. [73] provided a holistic overview of the various types of work-related communication patterns on Twitter, categorizing work-, profession-, organization-related tweets, and employee-public interactions. Table 1 summarizes the three main categories for the professional use of Twitter addressed in prior research. In the present study, we focus on the professional use of Twitter from the individuals' perspective and investigate whether the platform supports their work activities and professional networking.

To our best knowledge, serendipity in the professional use of Twitter is acknowledged in prior research but not empirically studied. While it has been established that individuals can experience work-related serendipity on Twitter [7, 17, 67, 77], little is known about what, in particular, enables it. In what follows, based on existing theories and frameworks, we provide a conceptual overview of the inherent characteristics of Twitter that may enable serendipity.

Table 1: Summarized categories of professional purposes of Twitter use.

Category	Description
Professional Identity Management [17, 56, 69, 73]	Identifying and promoting self as representative of an organization, team/group, or profession
Knowledge Sharing [18, 30, 73]	Documentation of daily work activities, sharing of professional opinions; engagement in professional discourse (e.g., question and answer type of communication)
Professional Networking [30, 69, 73]	Expert finding to fill in the knowledge gap; building connections with like-minded professionals within and beyond organizational boundaries; sustaining ties with co-workers

3 TECHNOLOGY CHARACTERISTICS OF TWITTER AS POTENTIAL FACILITATORS OF SERENDIPITY

According to Martin and Quan-Haase [43], the dynamism and liveliness of user-generated content and the various recommendation features embedded in the user interface enable divergent exploration of interesting others and trending topics. Building on this, we theorize that the technology characteristics of Twitter can enable both information and social serendipity. In the following, we operationalize Twitter technology characteristics by drawing from the perspective of functional affordances [25, 48]. Functional affordances are the system's characteristics that "help or aid the user in doing something" (in this study, achieving serendipity experiences in a professional context). To define technology characteristics and establish study measures, we adapt the framework by Ayyagari et al. [5] (see Table 2). While the investigated experiential phenomenon by Ayyagari et al. [5] was different, the level of abstraction in IT features analysis seemed appropriate for our analysis.

Table 2: The framework of technology characteristics and their manifestation in the context of Twitter use.

Features	Characteristic	Characteristic's manifestation on Twitter
Intrusive	*Presenteeism* – reachability and accessibility	Tweet, re-tweet, mention, 'like', 'follow', and direct messaging
	Self-disclosure – making the self known to others	Twitter profile information, tweets and likes
Usability	*Recommendation quality* – usefulness and relevance	Tweet-timeline, Explore, You might like, Who to follow and Trends for you features
Dynamic	*Pace of change* – frequency of changes in IT environment	Dynamism of the Twitter feed, users' actions and interactions, and dynamics of social network structures

Presenteeism is defined by Ayyagari et al. [5] as the degree to which technology makes people reachable for communication. The concept was primarily investigated as a cause for technostress, and a task disruption factor [5, 63]. However, as Brooks [8] demonstrated, presenteeism can also have positive effects when social media is used for gaining personal benefits. Presenteeism can thus be measured by the extent to which users perceive that technology makes them and other users reachable and accessible. In the context of Twitter use, it could be seen as a core characteristic that motivates the various uses of the service, hence providing chances for unexpectedly reaching useful content or contacts.

Self-disclosure relates to the system's capability to enable and encourage user profile creation and users' willingness to expose their information. Twitter has limited agency regarding how each profile turns out, while the user community introduces some norms. Prior research demonstrated that the core functionality of social networking sites necessitates extensive self-disclosure [76]. The user's perspective refers to managing online connections, knowledge, and opinion sharing. From the service perspective, self-disclosure enables personalization—delivering relevant recommendations and pushing specific content. On Twitter, self-disclosure is mainly enabled via user profiles where actors may reveal relevant information about themselves. The characteristic can be measured by how users perceive their Twitter profile as descriptive, comprehensible, and up-to-date.

By suggesting actions to the user, **recommendation quality** refers to the system's most proactive (high-agency) features. It is widely studied in computer science, outlining dimensions that constitute useful recommendations [54]. The first dimension—*accuracy*—stands for the recommendation agent's capability to predict the user's preferences [28]. Next, the *novelty* dimension refers to producing surprise—recommendations beyond the typical users' interest [74]. Finally, *diversity*—delivers heterogeneous recommendations to overcome the filter bubble and avoid monotonous suggestions [53]. The characteristic could be measured via subjective perceptions regarding content relevance and contact recommendations.

Pace of change is defined by Ayyagari et al. [5] as subjective perceptions regarding the rapidness of changes within the service environment. This characteristic builds on the users' actions and interactions within the service, enabling dynamism and liveliness. On Twitter, this characteristic is manifested through the fast-paced changes in users' feed, their interactions, and changes in the structures of ego-centric social networks caused by followership activities. Thus, this characteristic can be measured by the extent that users perceive the frequency of changes on Twitter.

4 METHODOLOGY

To address the research questions with a quantitative approach, we ran an international online survey in English. The survey enabled the collection of a diverse sample of responses to an extensive number of Likert-scale questions.

4.1 Measures Used in the Study

All the survey items except *professional use* were adapted from existing and validated scales. Please see the full list of the survey items in Table 3. **(1) Serendipity**, including *information serendipity* (see IS1-IS3 items in Table 3 and *social serendipity* (SS1-SS3) items were adapted from Lutz et al. scale [40]. We adjusted the scale

Table 3: Constructs and indicators of the study, including serendipity, Twitter characteristics, types of Twitter use, and personality characteristics.

Constract	α	Mean	SD	Item	Loading
				SERENDIPITY	
Social Serendipity	0.81	5.25	1.11	**SS1.** When using Twitter, I have made an accidental fortunate discovery of a contact that was useful for me	**0.716*****
				SS2. When using Twitter, I have encountered useful contacts that I was not looking for	**0.635*****
				SS3. When using Twitter, I have made an unexpected fortunate discovery of a contact that was useful for me	**0.608*****
Information Serendipity	0.86	5.09	1.19	**IS1.** When using Twitter, I have made an accidental fortunate discovery of content that was useful for me	**0.655*****
				IS2. When using Twitter, I have made an unexpected fortunate discovery of content that was useful for me	**0.631*****
				IS3. When using Twitter, I have encountered useful information, ideas, or resources that I was not looking for	**0.430*****
				TWITTER CHARACTERISTICS	
Presenteeism	0.84	5.61	0.89	**PRE1.** Twitter enables me to access others	**0.793*****
				PRE2. Twitter makes me accessible to others	**0.754*****
				PRE3. The use of Twitter enables others to have access to me	**0.708*****
				PRE4. The use of Twitter enables me to be in touch with others	**0.639*****
Self-disclosure	0.81	4.80	1.17	**SD1.** My Twitter profile contains all data asked by the service	**0.731*****
				SD2. My Twitter profile says a lot about me	**0.701*****
				SD3. My Twitter profile is comprehensive	**0.679*****
				SD4. My Twitter profile is up-to-date	**0.611*****
Recommendation quality	0.88	4.75	1.15	**RQ1.** The recommended content on Twitter fits my preferences	**0.859*****
				RQ2. The recommended contacts to follow on Twitter are relevant to me	**0.831*****
				RQ3. The recommended content on Twitter is relevant to me	**0.762*****
				RQ4. The recommended contacts to follow on Twitter fit my preferences	**0.726*****
Pace of change	0.70	4.74	1.01	**PC1.** There are frequent changes in the feed of other users' tweets	**0.826*****
				PC2. The users whose tweets I see in my feed changes frequently	**0.516*****
				PC3. The topics in my Twitter feed change frequently	**0.507*****
				TYPES OF TWITTER USE	
Professional use	0.79	3.77	0.90	**PU1.** I use Twitter to support my work activities	**0.940*****
				PU2. I use Twitter in my work	**0.698*****
				PU3. I use Twitter to support professional networking	**0.523*****
Receiving	0.77	3.57	0.73	**REC1.** Follow discussions related to particular hashtags	**0.767*****
				REC2. Check trending hashtags	**0.624*****
				REC3. Look for new Twitter users to follow	**0.612*****
				REC4. Read other people's tweets	**0.492*****
Broadcasting	0.83	3.43	0.76	**BR1.** Add photos and videos to tweets	**0.886*****
				BR2. Add hashtags to tweets	**0.669*****
				BR3. Send your own tweets	**0.524*****
				BR4. Mention other Twitter users in tweets	**0.445*****
				BR5. Share public content from other digital media in Twitter	**0.428*****
Interacting	0.80	3.25	0.81	**INT1.** Discuss with other Twitter users via Tweets	**0.844*****
				INT2. Engage in dialogue with other Twitter users	**0.795*****
				INT3. Discuss with other Twitter users via direct messages	**0.601*****
				PERSONALITY CHARACTERISTICS	
Openness to experience	0.84	5.44	1.20	... imaginative	**0.869*****
				... creative	**0.822*****
Neuroticism	0.76	3.75	1.39	... anxious	**0.778*****
				... easily upset	**0.774*****
				... moody	**0.620*****
Agreeableness	0.77	5.49	0.96	... warm	**0.778*****
				... kind	**0.709*****
				... sympathetic	**0.654*****
Conscientiousness	0.70	5.34	1.13	... organized	**0.800*****
				... self-disciplined	**0.657*****
Extraversion	0.73	4.31	1.41	... extraverted	**0.783*****
				... talkative	**0.736*****

to the context of work-related Twitter use by reflecting both the information and social perspectives; **(2) Twitter characteristics**, including *presenteeism*, *self-disclosure*, *recommendation quality*, and *pace of change*. *Presenteesism* items (PRE1-PRE4) adapted from Ayyagari et al. [5]; *self-disclosure* (SD1-SD4 items) from Lutz et al. [40]. *Recommendation quality* items (RQ1-RQ4 in Table 3) were taken from Knijnenburg et al. [35] scale, which we adjusted by distinguishing between content and contact recommendations. *Pace of change* (items PC1-PC3) originate from the scale of the dynamism of content by Heide and Weiss [26]; **(3) Types of Twitter use**, including *professional use*, *receiving* (passive consumption of social media content), *broadcasting* (active creation of the social media content), *interacting* (active engagement between users of social media). *Professional use* variable (PU1-PU3 items) represents the extent to which Twitter was used to accomplish work in general.

These items were designed by the authors and also used for screening. For the remaining items, the scale of active vs. passive use of online social networking sites was adapted [10, 11, 44]; **(4) Personality characteristics**, adapted from The Big Five Personality Traits [24, 38, 66], including *openness to experience*, *neuroticism*, *agreeableness*, *conscientiousness*, *extroversion*.

In general, we adjusted the scales to the context of the work-related use of Twitter. All the items were measured on a Likert-scale ranging from 1 (strongly disagree) to 7 (strongly agree) except for the types of Twitter use scales, which measured the frequency of use ranging from 1 (Never) to 5 (Every time).

4.2 Recruitment and respondents

We implemented the survey in English and used the Prolific[1] service for recruiting respondents in May 2018. We targeted individuals who use Twitter for professional purposes. To understand serendipitous experiences broadly, we did not limit to specific professions or industries. To ensure the validity of the sample we requested Prolific to screen their entire panel for eligible individuals who (1) worked in part- or full-time positions and (2) used Twitter for work (e.g., to support work tasks or professional networking) on a daily, weekly, or monthly basis. Only 1,080 of 122,435 from respondents pool fulfilled these two criteria. We started to invite people from that pre-screened pool to participate in the study. Within nine days we collected answers from 546 respondents.

Next, we took several extra measures to ensure the validity of the sample. First, we included survey questions on the professional use of Twitter to ensure that the respondents represent the intended population. Second, as we utilized Likert scale statements, including reversed statements, the responses with a standard deviation lower than 0.5 across all the questions were removed as a probable indication of inattentive responding.

Further, invalid responses were detected in open text fields, and the respondents who provided unrelated or inappropriate comments were omitted from the data. We also excluded responses given in less than three minutes as, on average, filling in the survey took 9 minutes. These filtering actions resulted in 473 responses that we considered valid for the analysis. The characteristics of the studied sample are presented in Figure 2. Gender, age, Twitter use experience, and followership information was also used to analyze serendipity antecedents.

4.3 Data Analysis

We used IBM SPSS Statistics[2] version 24 for all the analyses. First, we conducted an exploratory factor analysis (principal axis factoring[3]) to construct the latent variables (see Table 3). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy confirmed that the factoring of the items was possible with a value of 0.930 and a statistically significant Bartlett's test of sphericity (0.000). The extracted factors were allowed to correlate with each other by using the Promax rotation. Most of the item loadings (17/21, Table 3) were greater than 0.700, the threshold suggested by Chin [14], whereas the lowest loading was 0.574. Factor loadings greater than 0.400 have been considered acceptable in prior methodology literature [23]. We only omitted the following three items from three separate Big Five Personality Trait scales due to factor loadings lower than 0.400: "I see myself as ...unconventional (openness to experience-scale), ...dependable (conscientiousness-scale), ...enthusiastic (extraversion-scale)." The descriptive statistics of the factor analysis are shown in Table 3. The internal consistency of the scales was sufficient, as indicated by Cronbach's alpha value, which is >0.70 [65].

Second, we constructed three linear regression models to study the antecedents of information and social serendipity. We chose to preserve the range of the original survey items and calculated sum variables based on the means of the variables instead of using factor loadings as regression weights. The first model included gender, the age of respondents, and the number of followers and followees on Twitter. The second model extended the first model with five personality characteristics (*openness to experience, neuroticism, agreeableness, conscientiousness, extroversion*). The third model included all variables of the study.

Third, to analyze the Twitter use types, we constructed three linear regression models that included background, personality, and Twitter characteristics as antecedents of different types of Twitter use—*receiving, broadcasting, and interacting*.

5 FINDINGS

We first report descriptive statistics on the constructs to provide an overview of the data. Next, we provide findings on the factors that can explain information and social serendipity. Finally, we describe which background, personality, and Twitter characteristics are associated with different types of Twitter use.

5.1 Descriptive Statistics

Most respondents reported that they had experienced unexpected yet fortunate discovery of both content and contacts (See Figure 3). A similar positive attitude is also visible regarding Twitter characteristics. Respondents agree that Twitter makes them and other users accessible (presenteeism) and report their Twitter profile as complete, comprehensive, and up-to-date (self-disclosure). They also perceive the recommendations of both content and contacts on Twitter as effective (recommendation quality), and that Twitter is a dynamic platform (pace of change). As for personality characteristics, a large proportion of the sample reported being open to experience, agreeable, and conscientious. Attitude regarding being neurotic and extrovert is more evenly distributed, resulting in a median score of 4 (neutral).

The descriptive statistics on the types of Twitter use imply that a large portion of the sample represents active Twitter users (See Figure 4). Most respondents reported that they often use Twitter for professional purposes, for instance, to support work activities and professional networking (Med=4). The respondents reported almost equal frequencies of consuming (*receiving*, Med=4) and producing (*broadcasting*, Med=4) content on Twitter. At the same time, the respondents seem to less frequently engage in dialogue and discussions with other Twitter users (*interacting*, Med=3).

[1]Service for the online participant recruitment – https://www.prolific.co
[2]SPSS is a widely used program for statistical analysis – https://www.ibm.com/products/spss-statistics
[3]Principal axis factoring (PAF) that seeks the least number of factors that can account for the common variance (correlation) of a set of variables

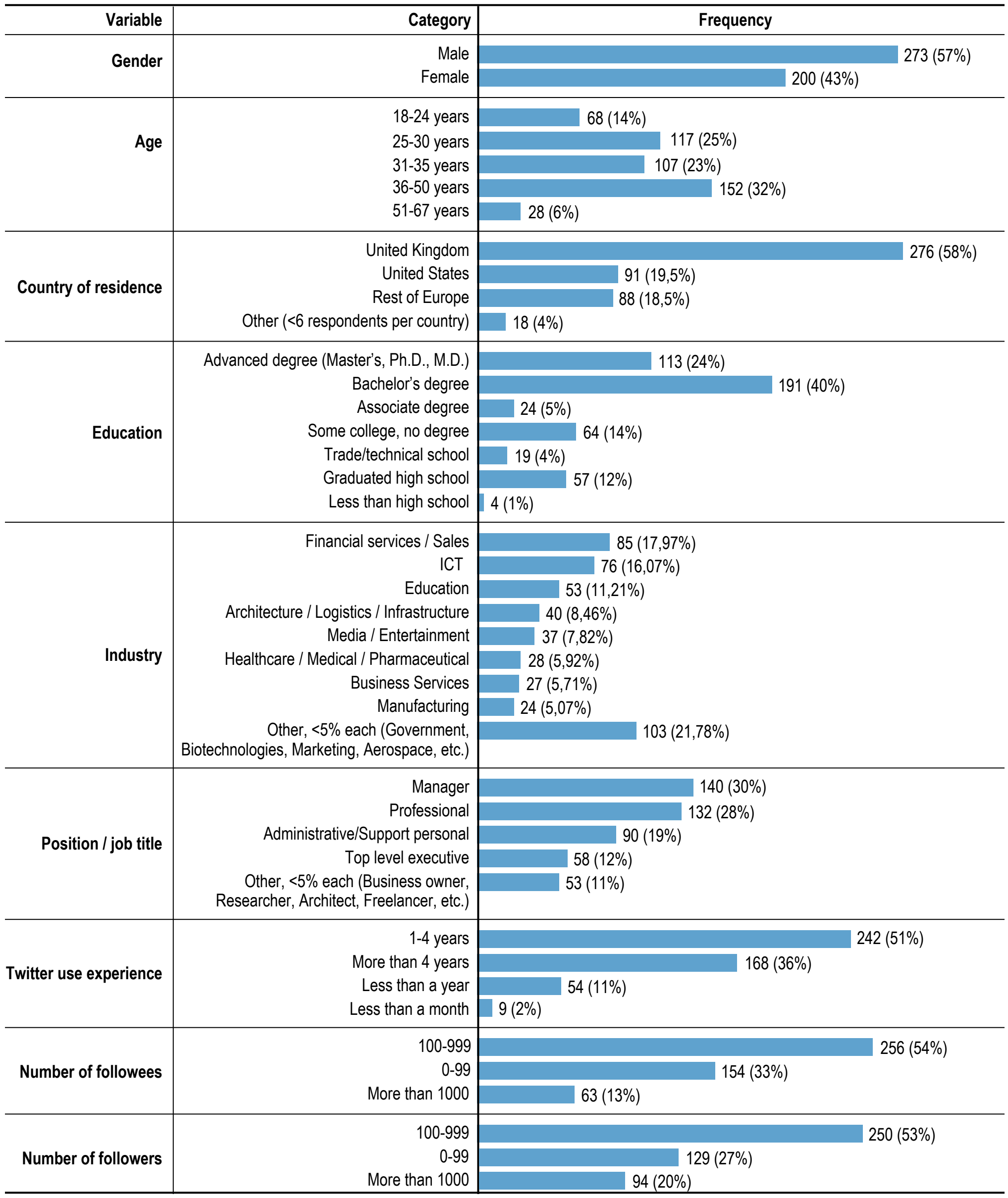

Figure 2: Sample characteristics (N = 473)

5.2 Antecedents of Information and Social Serendipity

Three linear regression models were utilized to reveal the antecedents of information and social serendipity on Twitter (See Table 4). From the first model (IS I & SS I), it is evident that the experience of Twitter use (0.223***), along with the number of followees (0.156*), associates with both information and social serendipity. It seems that the more the user is exposed to content on Twitter (over time and through followees), the higher are the chances for serendipity. The amount of variance extracted by the first model was low both in the case of information (3%) and social (2%) serendipity. That said, this effect does not explain the phenomenon well, which calls for investigating other factors.

The second model (IS II & SS II) adds two personality characteristics that can potentially associate with serendipity. This model performed slightly better regarding the amount of variance extracted as the model explained 13% of information serendipity and 11% of social serendipity. Accordingly, the more imaginative and creative (openness to experience, 0.272***), anxious, and moody (neuroticism, 0.070**) the user is, the higher the probability of encountering unexpected information. On the other hand, neuroticism does not have a significant effect (0.067) on social serendipity, while

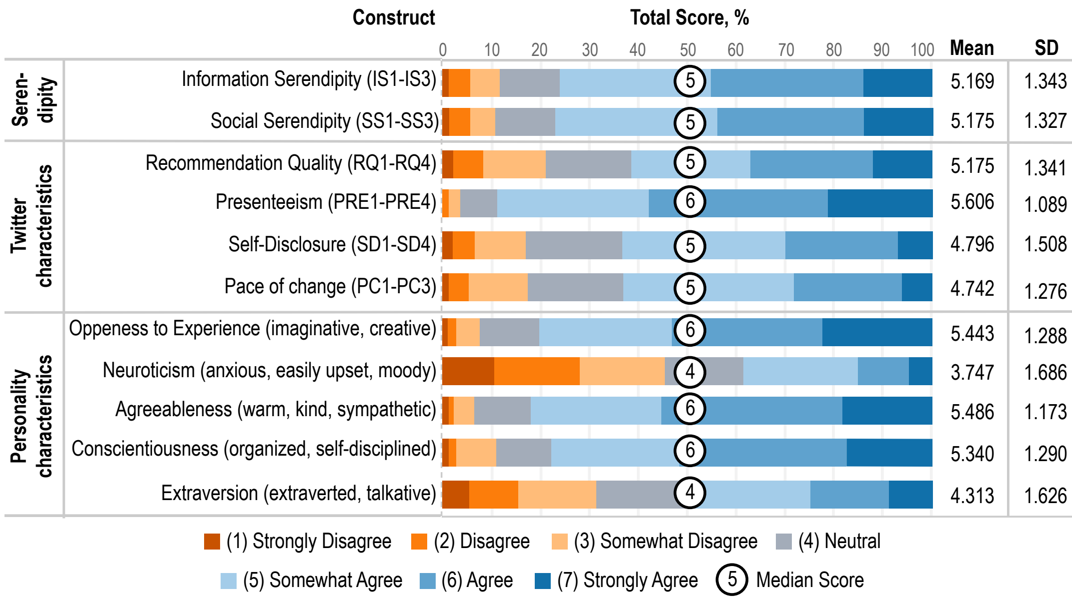

Figure 3: Descriptive statistics of the score distribution per constructs of serendipity, Twitter, and personality characteristics (%). N=473.

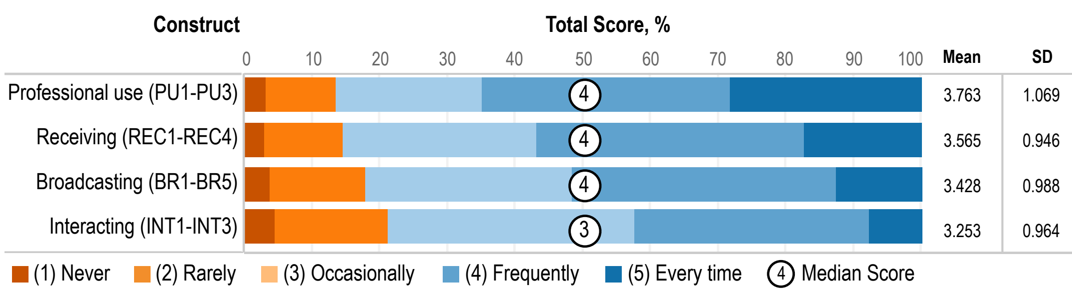

Figure 4: Descriptive statistics of the score distribution per constructs of Twitter use types (%). N=473.

agreeableness does (0.120*). The more warm, kind, and sympathetic the person is, the higher the probability of social serendipity seems.

The third model (IS III & SS III) explained 37% of information serendipity and 27% of social serendipity overall variance. When more variables are accounted for, the number of followees is no longer a significant predictor (0.89), and the number of followers is negatively associated with both information (-0.130*) and social serendipity (-0.161*). This suggests that individuals with a higher number of followers were less likely to perceive information and social serendipity than those with fewer followers. This might further consolidate the idea that mere exposure does not explain serendipity. The conscientiousness personality characteristic is similarly negatively associated with both information (-0.074*) and social serendipity (-0.113**). The less organized and self-disciplined the user, the higher the probability of encountering information and contacts serendipitously.

As for Twitter characteristics, only the extent to which users consider Twitter is making them reachable and accessible (presenteeism) seems to have a positive effect on information (0.593***) and social serendipity (0.508***), while recommendation quality, self-disclosure, and pace of change had no effect. This implies that many of the current Twitter features fail to support the emergence of this type of user experience—at least directly.

Using Twitter for professional purposes had a positive effect on both information (0.181***) and social serendipity (0.144**). The extent of using Twitter for passive actions (receiving (0.191**), e.g., reading tweets, checking hashtags) also has a positive effect on information serendipity. Engaging in discussions with other Twitter users (interacting) was negatively associated with information serendipity (-0.252***). This suggests that, within our sample, conversations with other Twitter users reduced the likelihood of perceiving unexpected fortunate discoveries of content.

Table 4: Antecedents of Information Serendipity (IS) and Social Serendipity (SS). N=473, unstandardized β values, CI= confidence intervals, * p <0.05, ** p <0.01, *** p <0.001

	IS I	SS I	IS II	SS II	IS III	SS III	95% CI	
	β (sig.)	β (sig.)	β (sig.)	β (sig.)	β (sig.)	β (sig.)	IS III	SS III
(Constant)	**4.365*****	**4.344****	**2.194*****	**2.147*****	.326	0.569	[-0.544, 1.195]	[-0.439, 1.577]
BACKGROUND CHARACTERISTICS								
Gender	-0.025	0.084	0.052	0.166	0.037	0.104	[-0.131, 0.205]	[-0.091, 0.298]
Age	-0.002	-0.006	-0.003	-0.006	-0.005	-0.008	[-0.014, 0.004]	[-0.018, 0.002]
Twitter use experience	**0.223*****	**0.154***	**0.201*****	**0.130***	**0.167*****	0.103	[0.047, 0.287]	[-0.036, 0.242]
Number of Followees	**0.156***	**0.195***	**0.171***	**0.199****	0.89	0.128	[-0.276, 0.016]	[-0.044, 0.299]
Number of Followers	0.004	0.028	-0.99	-0.080	**-0.130***	**-0.161***	[-0.059, 0.237]	[-0.330, 0.008]
PERSONALITY CHARACTERISTICS								
Openness to experience			**0.272*****	**0.253*****	**0.147*****	**0.158*****	[0.078, 0.234]	[0.067, 0.249]
Neuroticism			**0.070****	0.067	**0.080****	**0.075****	[0.015, 0.141]	[0.002, 0.148]
Agreeableness			0.087	**0.120***	-0.035	-0.018	[-0.144, 0.055]	[-0.134, 0.097]
Conscientiousness			0.029	-0.007	**-0.074***	**-0.113****	[-0.151, 0.012]	[-0.207, -0.018]
Extroversion			-0.002	0.041	0.001	0.025	[-0.065, 0.062]	[-0.049, 0.098]
TWITTER CHARACTERISTICS								
Presenteeism					**0.593*****	**0.508*****	[0.472, 0.696]	[0.378, 0.638]
Self-disclosure					-0.017	0.046	[-0.115, 0.080]	[-0.067, 0.159]
Recommendation quality					0.067	0.064	[-0.018, 0.162]	[-0.040, 0.169]
Pace of change					-0.031	-0.004	[-0.125, 0.077]	[-0.121, 0.113]
TYPES OF TWITTER USE								
Professional use					**0.181*****	**0.144****	[0.072, 0.286]	[0.020, 0.268]
Receiving					**0.191****	-0.038	[0.000, 0.318]	[-0.222, 0.146]
Broadcasting					0.060	0.007	[-0.084, 0.235]	[-0.179, 0.192]
Interacting					**-0.252*****	0.044	[-0.385, -0.108]	[-0.116, 0.205]
R squared	0.03	0.02	0.13	0.11	0.37	0.27		

5.3 Antecedents for Different Types of Twitter Use

As the different types of Twitter use have an effect on information serendipity especially, we investigated how the types of use might be associated with the other constructs (See Table 5).

The regression analysis results illustrate that the first and second models explain 40% of the overall variance in receiving and broadcasting, whereas the third model explains 34% of interacting. The data showcases a few background characteristics that might affect specific types of Twitter use. For instance, the more followees a user has, the more open she is to receiving (0.150***) behavior such as reading tweets, following and exploring hashtags, and seeking new Twitter users to follow. There is also a positive effect of the number of followers on broadcasting (0.225***) and interacting (0.166***). It is noteworthy that the findings only indicate a correlation, not a causal relation. One possible explanation for this correlation could be that the more followers one has, the more eager the user is to create and share content, mention others, and engage in discussions. Alternatively, the more one has shared content and interacted over time, the more followers they have managed to accumulate.

Openness to experience is associated with the receiving type of Twitter use (0.074***): the more open the person is, the higher the probability for her to be interested in exploring new information and contacts. Findings also illustrate that the less agreeable a person is, the more open she is to types of use such as receiving (-0.102***) and interacting (-0.071*). *Conscientiousness* had a relatively weak but positive association with interacting (0.053*). The more organized and self-disciplined a person is, the more open she is to discuss with other Twitter users. Furthermore, the personality characteristic of extroversion has a positive effect on receiving (0.044**), broadcasting (0.081***), and interacting (0.079**).

As for the Twitter characteristics, they all have an effect on different types of Twitter use. *Presenteeism* has a slightly lower effect on types of use than the other Twitter characteristics, as demonstrated by the positive effects on receiving (0.070*), *broadcasting* (0.064*), and *interacting* (0.078*). *Self-disclosure* has a positive effect on *receiving* (0.085***), *broadcasting* (0.196***), and *interacting* (0.183***), suggesting that exposing information about oneself is critical to all three forms of using Twitter. *Recommendation quality* seems to positively associate with types of Twitter use in terms of frequency of *receiving* (0.104***) and *interacting* (0.117***), yet it does not associate with serendipity directly. Furthermore, the *pace of change* (e.g., of Twitter feed) has an effect on *receiving* (0.246***), *broadcasting* (0.113***), and *interacting* (0.079**).

In summary, the findings imply that while Twitter characteristics were found not to have a direct statistical effect on serendipity, they associated with the ways of using the service, which in turn seem to support the emergence of serendipity. In other words, Twitter characteristics seem to relate to serendipity indirectly.

Table 5: Background, Personality, and Twitter Characteristics as antecedents of the Twitter use types. N=473, unstandardized β values, CI= confidence intervals * p <0.05, ** p <0.01, *** p <0.001

	Receiving β (sig.)	95% CI	Broadcasting β (sig.)	95% CI	Interacting (sig.)	95% CI
(Constant)	**0.636****	[0.078, 1.194]	**0.504***	[-0.073, 1.081]	0.213	[-0.341, 0.955]
BACKGROUND CHARACTERISTICS						
Gender	-0.065	[-0.172, 0.043]	**-0.114****	[-0.225, -0.003]	0.039	[-0.086, 0.164]
Age	-0.001	[-0.006, 0.005]	-0.003	[-0.008, 0.003]	-0.001	[-0.006, 0.007]
Twitter use experience	0.025	[-0.052, 0.103]	0.031	[-0.050, 0.111]	0.006	[-0.084, 0.096]
Number of Followees	**0.150*****	[0.056, 0.244]	0.000	[-0.097, 0.098]	0.070	[-0.039, 0.180]
Number of Followers	-0.046	[-0.136, 0.045]	**0.225*****	[0.131, 0.318]	**0.166*****	[0.061, 0.272]
PERSONALITY CHARACTERISTICS						
Openness to experience	**0.074*****	[0.024, 0.124]	0.039	[-0.013, 0.090]	0.001	[-0.057, 0.059]
Neuroticism	0.014	[-0.026, 0.055]	0.013	[-0.029, 0.055]	0.001	[-0.046, 0.048]
Agreeableness	**-0.102*****	[-0.165, -0.038]	-0.053	[-0.119, 0.012]	**-0.071***	[-0.145, 0.003]
Conscientiousness	0.034	[-0.018, 0.087]	0.034	[-0.021, 0.088]	**0.053***	[-0.008, 0.114]
Extroversion	**0.044****	[0.003, 0.084]	**0.081*****	[0.039, 0.122]	**0.071*****	[-0.024, 0.118]
TWITTER CHARACTERISTICS						
Presenteeism	**0.070***	[-0.002, 0.141]	**0.064***	[-0.010, 0.137]	**0.078***	[-0.005, 0.161]
Self-disclosure	**0.085*****	[0.024, 0.145]	**0.196*****	[0.134, 0.259]	**0.183*****	[0.113, 0.252]
Recommendation quality	**0.104*****	[0.047, 0.161]	0.046	[-0.013, 0.105]	**0.117*****	[0.050, 0.183]
Pace of change	**0.246*****	[0.185, 0.307]	**0.113*****	[0.050, 0.176]	**0.079****	[0.009, 0.150]
R squared	0.40		0.40		0.34	

6 DISCUSSION

This study investigated technology characteristics that can contribute to serendipity experiences and how they associate with Twitter use types. The findings provide several empirical contributions relevant to research on serendipity, computer-supported cooperative work, and information systems:

(1) We consolidate the relevance of the serendipity phenomenon within the context of Twitter use for professional purposes – respondents reported that they experienced both information and social serendipity. While the types of Twitter use in relation to serendipity were acknowledged and tentatively studied in prior research [7, 46, 77], our findings extend the empirical understanding of existing statistical associations, particularly in the context of professional use of Twitter. The use of Twitter for professional purposes was strongly associated with serendipity: it is about one's orientation toward or the practice of using it for specific purposes.

(2) This is the first study that investigates Twitter characteristics as functional affordances of serendipity, demonstrating technology's limited role in shaping serendipity. According to this sample and analysis, serendipity is more explained by factors relating to individual characteristics, such as personality and behavior, that is, how Twitter is used in work.

(3) In contrast to prior research that focuses solely on information serendipity [39, 46], we extend the understanding of social serendipity. The analysis contrasts information serendipity and social serendipity by identifying differences between factors that explain them. The findings generally show that the regression models explain more variance in information serendipity than social serendipity.

(4) In contrast to prior research, which only admits the importance of personality traits in serendipity [46], our study offers extensive empirical data on the associations between serendipity and personality characteristics in the context of Twitter use.

In what follows, we elaborate on the specific takeaway findings by reflecting on the study's contributions. We conclude by stating the limitations and pointing out practical implications and opportunities for future research.

6.1 Discussion of the Key Findings

6.1.1 The Role of Twitter Characteristics. To our knowledge, this is the first study that investigates Twitter characteristics as functional affordances that might contribute to serendipity experiences. We assume that the technology characteristics on Twitter (especially *recommendation quality*) are intended to enrich the user experience in many ways, including the facilitation of serendipity. However, our findings imply that the studied characteristics, apart from *presenteeism*, fail to do that, at least through a direct statistical association.

A possible explanation for such a finding could be the Twitter mechanisms of pushing the content to the users. Notably, the Twitter feed was previously organized in reverse-chronological order and only featured the followees' tweets. Nowadays, the feed displays the tweets in a personalized manner according to inferred user preferences [51, 72]. Even if a user does not have many followees, the system will provide an endless stream of content based on the recommender system (also from outside one's connections). Furthermore, the higher the number of followees users have, and the more active they are, the higher the probability that recommendations will be based on their established interest sphere. This, in turn, might result in "echo chambers" rather than serendipity, leading to interactions with similar ideologies and thoughts with fewer opportunities for new or controversial standpoints to emerge [19]. That said, the analysis indicates that Twitter characteristics are central antecedents to the different ways of using the platform. This implies that Twitter characteristics can be indirectly related to serendipity, at least regarding information serendipity.

6.1.2 The Role of Types of Twitter Use. Although it could be expected that using Twitter for *receiving* (e.g., following specific hashtags) and *interacting* (e.g., engaging in discussions) would support social serendipity, the data did not show such an effect. Different ways of using Twitter primarily associate with information serendipity. Especially the use of Twitter for *receiving* was found to increase the chances of experiencing information serendipity. Somewhat counter-intuitively, *interacting* with others by taking part in discussions seems to be negatively associated with information serendipity. We suggest that a possible reason for this negative relationship is that users in our sample engage in discussions with others who are already familiar with them. Hence, the user is less likely to encounter new information. This is because individuals with stronger ties, that is, they already are acquainted with each other and have a shared history of interactions, usually possess overlapping knowledge due to shared background and similar interests [19]. *Broadcasting* type of use does not associate with serendipity at all. Such findings imply that the more the platform knows about the user due to active content production, the more likely one ends up in a silo of like-minded actors—consolidating the theory of echo chambers [19, 53].

6.1.3 The Role of Personality Characteristics. The analysis shows that, regarding the personal factors, *openness to experience* and *neuroticism* are favorable for both information and social serendipity. The identified association between openness to experience and serendipity supports prior research that has conceptualized that people should have an open or "prepared" mind to experience serendipity [20, 45]. We suggest that *neuroticism* plays an essential role because neurotic people tend to mind-wander and shift their attention to task-irrelevant thoughts [64]. Such personality quality might be of benefit to experience serendipity because it can drive a person's ability to be receptive to unexpected connections and patterns, which is one of the suggested strategies to experience serendipity [42]. Here, we wish to note that *conscientiousness* (being self-disciplined and organized) may not be favorable for serendipity. Being conscientious means that a person would be task-oriented and have less space for idle moments and an associative state necessary for experiencing serendipity [42, 47]. Hughes et al. [29] suggest that the use of Twitter to socialize correlates with lower conscientiousness: the fact that average Twitter users possess a broad spectrum of interests and are keen on socializing would decrease the time for their goal-directed behavior.

6.2 Limitations

With the benefit of hindsight, we acknowledge some limitations in our study. First, the study was based on self-reported subjective experiences collected with a cross-sectional survey, which may not give an entirely truthful and generalizable picture of the actual serendipity experiences in the target context. Using Prolific to recruit respondents could bias the findings as such online platforms were criticized for providing poor-quality data and samples [15]. For instance, most of our respondents were from the United Kingdom and Western countries. There might be cultural factors related to the use of Twitter and the perception of serendipity that we wish to address in future research.

Despite the limitation of the sample, using Prolific enabled us to find suitable participants for the study, ensuring that each participant used Twitter for work and could answer the survey anonymously. Moreover, according to Newman et al. [49], Prolific provides a more diverse participant pool and ethical pricing for incentives compared to other online survey platforms. Additionally, we employed pre-screening and attention checks to ensure data quality, which are key recommendations for running research on platforms like Prolific [49].

Second, the study addressed serendipity in the context of professional use of Twitter with specific technological characteristics and user community. As such, we believe that the insights on the antecedents of serendipity may not be transferable to other social media services used in work- or non-work settings. Third, the participants were rather eager to consider their experiences serendipitous. With such a study setup, we could not control how strong serendipity experiences the participants had, and the measures could be said to set a relatively low threshold for what counts as serendipity.

6.3 Practical Implications and Future Research Topics

The results of this study can inform organizations and individuals who utilize Twitter for work purposes. Serendipity experiences have been found essential for task innovation in the context of Twitter use [61]. Thus, understanding serendipity antecedents can help organizations strategize the use of Twitter for professional purposes to induce serendipitous information discoveries and social networking. The findings also could inform new measurable algorithmic dimensions for researchers and designers in Information Retrieval and Recommender Systems fields. A minor role of technology in explaining serendipity calls for revisiting computational approaches and mechanisms on social media services. We encourage other researchers to pursue the identification of both internal characteristics and designable service features for inducing experiences of serendipity—particularly social serendipity. The findings reveal that the factors related to the individual (i.e., personality) play an essential role in using Twitter. These factors are harder to influence by design choices because they are inherent to the user. Instead, system design mindful of serendipity could aim to support such experiences with strategies that foster certain personality qualities responsive to the perception of serendipity experience [42]. The study also implies that influencing serendipitous experiences are hardly controllable by design choices. Therefore, rather than seeking design solutions that deliver "serendipity on a plate" [42], we call for design endeavors that aim to facilitate value-adding types of use. For instance, altering how information can be received or broadcasted or how conversations can be initiated with others might increase the chances of serendipity. That said, it is essential to set users in an explorative state of mind, and a promising approach in that regard is to apply diversity-enhancing strategies [27, 33] that can foster divergent exploration activities by pushing content and contacts that are beyond typical users' interests. Therefore, we encourage searching for new ways to boost interaction between individuals who are not well-acquainted with each other. This could potentially mitigate the unexpected finding that interacting with others reduces information serendipity. We also suggest that promoting different ways of using Twitter is helpful as it may indirectly lead to serendipity.

7 CONCLUSIONS

The emergence of serendipity can be regarded as a positive indicator of the overall service quality in many IT services and, therefore, a fundamental design goal. While Twitter can be considered a potent platform for serendipity, there is little understanding of what particular characteristics contribute to such experiences. After identifying potentially relevant Twitter characteristics, we collected and analyzed survey data to measure how the characteristics are associated with information and social serendipity experiences. The study offers an analysis of the factors contributing to serendipity in the context of the work-related use of Twitter. Additionally, we extend prior research by analyzing antecedents of serendipity to various technology and personality characteristics and types of Twitter use. The findings illustrate that serendipity is more explained by personality characteristics and types of Twitter use. Regarding Twitter characteristics, only presenteeism has a significant effect on subjective experiences of serendipity. Thus, this study illustrated the complex nature of serendipitous experiences in the professional use of Twitter, which calls for identifying new serendipity-inducing mechanisms.

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