Investigating the Effects of Implicit and Explicit Personalization on Perceived Credibility

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Abstract
Personalizing computer systems (such as Academic Social Networking Sites) can improve positive user perceptions, particularly credibility perceptions of that system. Earlier research has identified two broad personalization approaches: Implicit and Explicit personalization. Moreover, applying the wrong personalization approach may negatively affect users' perceptions of the system's credibility. Yet, the evidence that earlier research provides for the relevance and importance of the different personalization approaches on perceived credibility in system design is limited. This study explores which of the two personalization approaches is most important and could be prioritized when designing systems to improve credibility perceptions. Academic Social Networking Sites (ASNSs) users' perceptions of implicit and explicit personalization and system credibility are gathered via survey and analyzed using Partial Least Square Structural Equation Modeling. We find that whereas Implicit personalization has a positive influence, Explicit personalization negatively influences users' credibility perceptions. Furthermore, the Importance Performance Map Analysis (IPMA) reveals implicit personalization as the better-performing and more important approach for promoting credibility perceptions on ASNSs. Based on the results, this study recommends further investigations into how personalizing the personalization approaches for different users may affect their credibility perceptions.

Keywords
personalization, persuasive systems, credibility

1. Introduction

The desire to tailor tools, equipment, and products to meet individual needs is a longstanding concept. Throughout history, artisans, craftsmen, and businesses have crafted custom-made items (such as clothing and furniture) specifically designed to enhance personal experiences and better suit individual preferences. In today's digital landscape, personalization continues to play a crucial role in shaping user experiences. Many e-commerce platforms in the United Kingdom and the United States have increasingly incorporated personalization techniques to enhance user satisfaction and foster loyalty [1, 2]. Similarly, many online social networks

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employ artificial intelligence techniques to tailor content based on various factors, such as location, time of day, and recent interactions, to ensure that the content remains relevant to users [3]. Thus, personalization techniques have been pervasively adopted to enhance user experience in many digital environments. Consequently, research attention on the concept of personalization has increased.

The concept of personalization has been viewed differently by different fields. In management science and marketing, personalization is defined as delivering targeted solutions to a customer based on the customer's personal information [4]. In the field of estate management, personalization is the modification of one's environment to reflect the occupant's identity or imprint [5]. From a computer science perspective, personalization is mainly concerned with the application of rules to design varying sets of features and interfaces [6]. In this current study, personalization is defined as changing the functionality and behavior of an information system to increase its relevance to an individual or a category of individuals. This definition is based on how earlier studies (e.g., [7, 8]) have defined personalization in the field of Human-Computer Interaction (HCI). Relevant HCI literature [9, 10] demonstrates two main personalization approaches (i.e., Implicit, and Explicit). With the Implicit Personalization approach, the system automatically adjusts itself (i.e., behavior and interaction), in a way that is intended to support the user's needs. On the other hand, Explicit Personalization requires users to utilize configuration mechanisms provided by the system to specify how they want the system to behave [10]. Implicit and Explicit Personalization is synonymous with adaptive – adaptable [11], dynamic – static [12], or weak - strong personalization [13] as used in some studies. Regardless of the terms used, Implicit Personalization is system-controlled, whereas Explicit Personalization is user-controlled [9].

Existing literature posits that personalizing computer systems is an effective means of accommodating the differences between user needs and requirements [14]. When computer systems are personalized, users perceive them to be tailored fit for them, which positively affects their attitude towards the system [15]. Papakostas et al., [16] also showed that personalization can enhance users' perception of the system's usability and effectiveness. Personalization can therefore be harnessed as a tool to project positive user perceptions such as credibility. However, research into how personalization affects different user perceptions is still infant. Existing studies (e.g., [17]) have primarily focused on user preferences between Implicit and Explicit Personalization. There is limited research on how the personalization approaches affect specific user perceptions, particularly credibility. Such an understanding is important because credibility is a key factor that influences users' trust and engagement with computer systems [18]. If users perceive a system as credible, they are more likely to trust its recommendations, rely on its functionality, and remain engaged over time [19]. Moreover, the design principles implemented in a computer system can trigger unintended negative outcomes [20]. It is therefore important for designers who prioritize credibility to understand which approach can achieve the intended objective. This current study thus examines users' perceptions of Implicit and Explicit Personalization approaches implemented on Academic Social Networking Sites (ASNSs), and how these approaches influence users' credibility perceptions. This study further examines the importance and performance of Explicit Personalization and Implicit Personalization on users' Perceived Credibility of ASNSs using the Importance Performance Map Analysis (IPMA).

The findings from this study will offer valuable insights for designers and developers seeking to optimize user experience and enhance users' credibility perceptions of their systems. As personalization techniques become more prevalent, it is essential to understand their effects to avoid potential pitfalls, such as decreased trust or user dissatisfaction. Furthermore, employing the Importance Performance Map Analysis (IPMA) to evaluate the significance and effectiveness of these personalization approaches provides a rigorous methodological framework for assessing their impact. Thus, the study will contribute to both theoretical knowledge and practical guidelines, helping developers create more effective computer systems that better meet users' needs and preferences. The next section presents related works. This is followed by the research method, analysis, and discussion of findings.

2. Literature Review

2.1. Related Works

The design principles and strategies implemented in a computer system (e.g., ASNS) can affect users' attitudes and behavior toward the system [21]. In line with this, existing studies indicate that implementing design strategies that project system credibility can positively influence user perceptions and intentions [22, 23]. This implies that an understanding of how credibility principles can be implemented in system design is essential for influencing system use and, hence, the need to be examined. Credibility is believability [24]. In another definition, credibility is the extent to which a computer system is worthy of trust and perceived to have expertise [21]. A user's credibility perception is informed by his/her evaluation of the characteristics of a computer system (e.g., ASNSs) [23]. Personalization (which is a system characteristic) can therefore influence users' credibility perceptions. It is thus important to understand how personalization influences users' credibility perceptions. This is because lower ratings of system credibility result in negative user attitudes toward the system and discourage system use [25]. On the other hand, when users perceive a system to be credible, the system is perceived to be more effective [26], and more likely to be used continuously [27].

Yet, there is a lack of clear understanding as to how personalization can be implemented in system design to promote credibility perceptions. Evidence as to which of the two personalization approaches is more effective is lacking. Rather, existing studies have compared user preferences for personalization approaches. For example, Parra and Brusilovsky [17] explored how user-controllable personalization influences user perceptions of a recommender system. The study concluded that when users are allowed to control personalization, it improves their overall experience, and they are more likely to accept the recommendations provided by a recommender system. Also, Findlater and McGrenere [11], compared the efficiency and user preferences for adaptive (i.e., Implicit) and adaptable (i.e., Explicit) user interface menus. The results from the study indicated that adaptable menus are mostly preferred and more efficient compared to adaptive menus. In a different study, Orji et al., [9] compared the effectiveness of and user preference for system-controlled (i.e., Implicit) and user-controlled (i.e., Explicit) personalization approaches implemented in a persuasive health game. The study concluded that the implicit personalization approach received high preference as it reduced system complexity.

The results from earlier studies show inconsistent and varying preferences for the personalization approaches. Admittedly, the inconsistent result may have been caused, for instance, by the differences in the domains these studies were conducted. This further implies that the implementation of personalization approaches may have different effects under different conditions. Further, these results do not provide adequate direction for what designers should consider when choosing a suitable personalization technique for their systems. Hence, these existing studies cannot form the basis for informed decision-making on which personalization approach should be prioritized to improve credibility. Unlike the above-mentioned existing studies, this current study attempts to address the existing limitations by providing adequate information on the specific effectiveness of the personalization approaches on users' credibility perceptions. Likewise, this current study employs the IPMA to understand the relative performance and importance of the two personalization approaches on the Perceived Credibility of ASNSs using the Importance Performance Map Analysis (IPMA). Thus, with the IPMA this study provides an additional layer of methodological rigor that helps to establish how each of the personalization approaches perform and where improvements are needed.

2.2. Importance Performance Map Analysis

The IPMA (see Figure 1) (also referred to as priority map analysis) is an analytical technique that augments faster, strategic, and quality decision-making [28]. IPMA highlights the main factors that are critical for desired results. IPMA is represented using a four-quadrant square matrix with performance represented on the x-axis and importance on the y-axis. Quadrant 1 signifies high performance and importance, Quadrant 2 shows low performance and high importance, Quadrant 3 indicates low attributes in both performance and importance and Quadrant 4 represents high performance but low importance. In decision-making, concepts that are represented in Quadrant 1 are regarded as the most impactful on the observed phenomenon [29]. That is, the IPMA helps to identify from a variety of concepts, the ones that should be prioritized to improve a certain target concept. The IPMA is important for practical studies (as in the case of this study) that identify the different impacts that certain dimensions of a concept have on an observed phenomenon. IPMA has proven to be useful in fields including information security [30], tourism [31], banking [32], and hospitality [33]. Therefore, in this study, the IPMA is applied to compare which of Implicit and Explicit personalization is most influential in terms of importance and performance on users' credibility perceptions in ASNSs.

2.3. Academic Social Networking Site

ASNSs are online spaces specially designed for academic and professional collaborations and networking [34, 35]. Popular ASNSs include ResearchGate, Google Scholar, and Academia.edu. ASNSs allow users to create and share content, ideas, and with other users. They assist academics to find jobs, access publications, and support each other through knowledge sharing and social interactions.

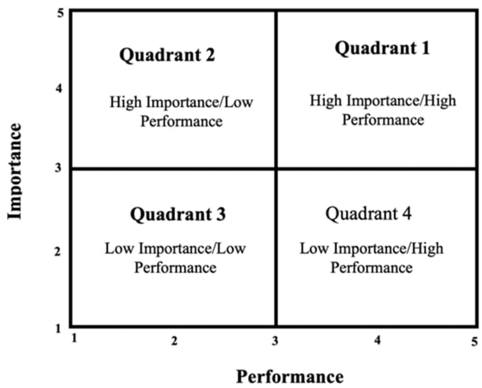

Figure 1. Importance-Performance Matrix

With the increasing relevance of ASNSs in the research community, some institutions have started to include ASNSs' contributions as a measurement metric for research impact, and in some cases for promotions and tenure review processes [36]. Therefore, using ASNSs to boost one's research impact has become necessary. Some ASNSs implement personalization to optimize and increase system effectiveness. For example, Academia.edu is designed to automatically adapt the content shown on a user's newsfeed to reflect their previous searches and reading patterns. ResearchGate also allows users to specify categories of content they prefer on their newsfeed. It is important that designers of ASNSs understand the implications of their design approach. Most of all, it is essential that they prioritize the right personalization approach in their design to project positive user perceptions of the system. This study makes two main contributions: (i) we show which personalization approach should be prioritized when targeting improved user credibility perceptions (ii) we are the first to extend the application of IPMA into the ASNSs domain. This next section discusses the research methods.

3. Method

3.1. Materials

A survey research design approach was used in this study. Participants' views and opinions on concepts: (i) implicit personalization, (ii) explicit personalization, and (iii) perceived credibility of ASNSs were gathered using a questionnaire. Each concept had at least three (3) questions ranked on a seven-point Likert scale ranging "Strongly Disagree (1) to "Strongly Agree (7)". The questions were adapted from prior studies [10, 37, 38] to suit the context of this study.

3.2. Procedure

The participants for the study were selected using convenience and snowball sampling. An invitation was sent to potential participants through an email list from the University of Ghana and other professional bodies (e.g., BCS-HCI). The invitation explained that the study was purely academic, and participants' responses would be anonymous. Interested participants were asked to click on a link that directed them to the questionnaire. In the questionnaire, participants were asked to provide their demographic information such as age range, gender, educational background, whether they use ASNSs, which ASNSs they use, and how frequently they use them. Next, they were tasked to provide their views and opinions on the extent to which they disagreed or agreed with certain question items. After these questions were answered, they were asked to submit their responses and were thanked. No rewards were given for participation.

3.3. Participants

Participation in this study was purely voluntary. Although a total of 140 responses were received, 133 responses were used for the analysis. Responses from 7 participants were removed because they indicated they had not used ASNSs in the past year. The majority (51%) of the responses used ASNSs (including ResearchGate, Academia.edu, LinkedIn, etc.) at least once a week. More than half (121 of 133) of the participants use ASNSs for Research purposes. The age distribution showed that majority (67%) of the respondents were below 35 years, 31% were between 35 to 55 years, and the remainder were above 55 years.

4. Analysis

The Partial Least Square Structural Equation Modelling (PLS-SEM) technique was used to evaluate the hypothesized model. PLS-SEM is appropriate for this study because of its robustness to multivariate errors and efficacy in evaluating predictive models [32]. This approach will enable the study to estimate the relationship between the understudied concepts and offer design implications. The next section discusses the measurement and structural model evaluations.

4.1. Measurement Model

The measurement model in PLS-SEM analysis is used to assess the validity and reliability of the items used to measure the model. The techniques used to assess the measurement model were item reliability, internal consistency, convergent validity, discriminant validity, and collinearity. A minimum threshold of 0.7 was used to assess item reliability, and internal consistency (measured with Cronbach's Alpha, Rho_A, and composite reliability). The convergent validity was assessed with Average Variance Extracted (AVE) using a minimum threshold of 0.5. The possibility of collinearity was evaluated using a Variance Inflation Factor (VIF) maximum threshold of 3. Table 1 shows the summary item reliability, internal consistency, convergent validity, discriminant validity, and collinearity of model constructs. Finally, discriminant validity was assessed with Heterotrait-Monotrait Ratio (HTMT) using a maximum threshold of 3. All thresholds were in line with Hair and Sarstedt's [39] recommendations.

4.2. Structural Model

The significance of the proposed relationships is evaluated in this section. The Bootstrap (5000 re-samples) technique was used to examine the relationships. Using a one-tailed t-test, a p-value less than 0.05 was considered a significant relationship. The results of the structural model analysis are shown in Figure 2. Along with the p-value, Cohen's [40] effect size (f) criteria were used to determine whether the effects of the independent variables were strong (≥ .35), medium

(≥ .15), weak (≥ .02), or irrelevant (<.02). The summary of the relationships is illustrated in Table 3.

Table 1.
Construct Reliability and Validity

Constructs and Items	**Outer Loadings**	**VIF**
Explicit Personalization (AVE = 0.806, CA = 0.921, Rho_A = 0.947, CR = 0.943)		
EXP 1: The ASNS(s) that I use permit me to change the features such that I perform the required tasks	0.904	1.073
EXP 2: The ASNS(s) that I use enable me to personalize them to fit my goals.	0.874	1.691
EXP 3: The ASNS(s) that I use allow me to change them to fit my personality.	0.903	1.729
EXP 4: I am able to change the content of the ASNS(s) that I use to meet my interest and goals.	0.910	1.926
Implicit Personalization (AVE = 0.766, CA = 0.897, Rho_A = 0.904, CR = 0.929)		
IMP 1: The ASNS(s) that I use adapts itself to fit my needs.	0.787	1.891
IMP 2: The ASNS(s) that I use provides information that benefits me in performing my tasks.	0.925	1.435
IMP 3: The ASNS(s) that I use offer content that is of interest to me.	0.901	1.987
IMP 4: The ASNS(s) that I use know and understand what I want.	0.883	1.597
Perceived Credibility (AVE = 0.884, CA = 0.934 Rho_A = 0.938, CR = 0.958, R^2 = 0.416)		
CRED 1: I trust all the information I receive on the ASNS(s) that I use.	0.910	1.168
CRED 2: In my opinion the content on the ASNS(s) that I use is believable.	0.967	1.825
CRED 3: Overall, I consider the information I receive on the ASNS(s) that I use as credible.	0.944	1.050

NB: CA; Cronbach's Alpha, CR; Composite Reliability, AVE; Average Variance Extracted, VIF; Variance Inflation Factor

Table 2.
Discriminant Validity using HTMT

	Credibility	**Explicit**	**Implicit**
Credibility			
Explicit	0.134		
Implicit	0.687	0.435	

The results show that Explicit and Implicit Personalization collectively explained 41.6% (R^2=0.416) of the variance of Perceived Credibility. This means that Explicit and Implicit

Personalization contributes close to half of users' credibility perceptions. Moreover, we found that both Implicit and Explicit Personalization are significant determinants of Perceived Credibility. However, whereas Implicit Personalization had a significant and strong positive effect on Perceived Credibility (β = 0.689; $p < 0.00$; $f^2 = 0.683$), the effect of Explicit Personalization on Perceived Credibility was reversed. Specifically, Implicit Personalization had a significant but weak negative effect on Perceived Credibility (β = -0.146; $p < 0.019$; $f^2 = 0.031$). This means that whereas implementing Implicit Personalization in a system promotes positive credibility perceptions, Explicit Personalization will reduce users' credibility perceptions (see Table 3).

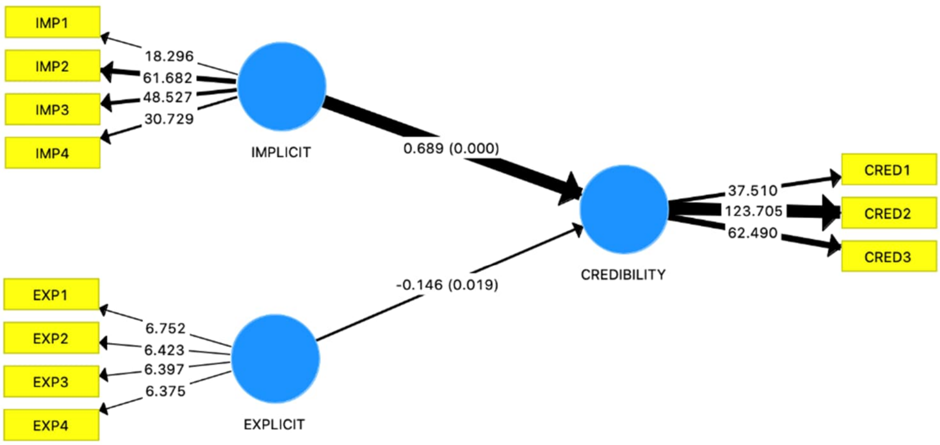

Figure 2. Structural Model

Table 3.
Path Coefficients and Effects

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**f^2**
Explicit -> Credibility	-0.146	-0.130	0.071	2.068	0.019	0.031
Implicit -> Credibility	0.689	0.686	0.069	9.913	0.000	0.683

The Important Performance Map Analysis (IPMA) from SmartPLS 3.0 was also implemented to analyze which of the two approaches respondents perceived to be most important in influencing credibility perceptions. The results from Table 4 and Figure 3 illustrate that Implicit Personalization has both the highest importance (0.689) and performance (66.319) scores. This means that when Implicit Personalization on ASNSs is increased by 1 unit point, users' credibility perceptions would also increase by 0.689. This further suggests that implicit personalization as implemented on ASNSs (such as ResearchGate) is acceptable to users. On the other hand, although Explicit Personalization is relatively important, its performance in influencing credibility perceptions is low. That is, an increase in Explicit Personalization by a unit point decreases credibility perceptions by 0.146. From these results, there is a need for system designers to improve on the explicit personalization techniques of ASNSs and how they are presented to users.

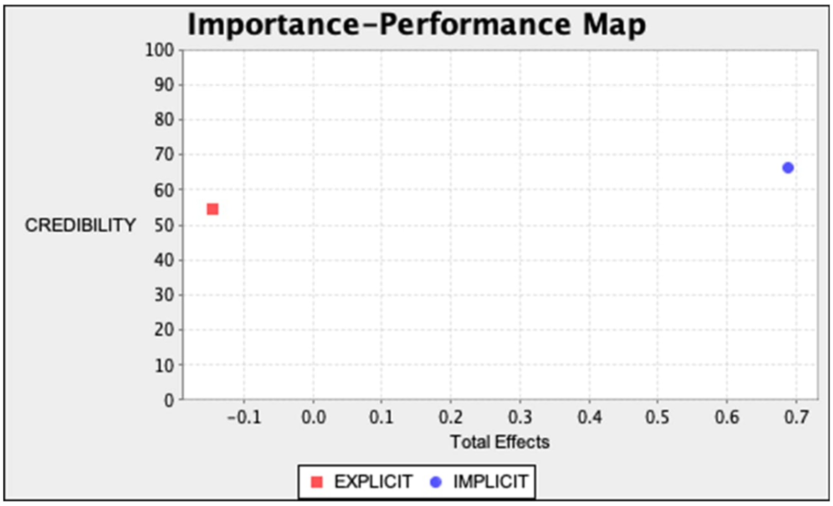

Figure 3. Importance Performance Map

5. Discussion

Personalization as a system design concept has attracted increasing attention from both academia and industry due to the growing realization of its importance in increasing overall system acceptance and user experience [41]. This argument holds from extant studies that show that personalized systems improve system usability and usefulness [16], [17] and promote positive user attitudes and perceptions [26, 27, 37]. Nevertheless, evidence of which personalization approach is most important and effective for promoting specific user perceptions (i.e., credibility) is missing in the existing literature. This study evaluated which of Implicit and Explicit personalization approaches is most important for promoting users' credibility perceptions using the Importance Performance Map Analysis (IPMA) technique in Partial Least Square Structural Equation Modelling (PLS-SEM). This study is perhaps the first to compare the two personalization approaches in the ASNSs and using the IPMA.

The study found that whereas Implicit Personalization positively influenced Perceived Credibility, Explicit Personalization had a negative effect on Perceived Credibility. Specifically, users perceived ASNSs which automatically adapt its features to fit their needs to be credible. On the other hand, when users are offered the chance to change ASNS features such that they fit them, they perceive ASNSs as less credible. This could be due to users' expectations of the system. Indeed, with the recent proliferation of technological innovation such as Artificial Intelligence (AI), users' engagement with some technologies has been seamless and requires less effort. Perhaps, ASNS users expect these systems to automatically know their needs and what is good for them. Rather, when users are required to make specifications themselves, they may perceive the system to be less proficient or knowledgeable. This may cause them to rate the system as less credible. System designers who perceive explicit personalization as essential for their designs may cure such mentality by offering educational platforms that educate users as to why they expect them to specify the system's behavior themselves.

Also, the IPMA results reveal that implicit personalization is the most valuable approach for promoting credibility perceptions in ASNSs. Precisely, implicit personalization had higher ratings in terms of performance and importance compared to explicit personalization. This means that implicit personalization should be prioritized in ASNS design to increase perceptions credibility. This result reflects the operations of many ASNSs. Currently, ASNSs (e.g., ResearchGate) employ implicit personalization by streamlining content for users based on their activities on the sites, people they follow, their co-authors, or even authors they have cited in their publications. Therefore, users perceive that such ASNSs provide content that is relevant to their needs. Research also shows that users will perceive a system to be credible when it supports their primary tasks [21, 37, 42]. Conceptually, this distinction underscores the psychological mechanisms underlying user engagement with personalization. Explicit personalization provides users with agency and control, which can enhance perceived usefulness and trust. On the other hand, implicit personalization operates in the background, requiring minimal user intervention, and may not be consciously acknowledged as influential. Our findings suggest that organizations should prioritize optimizing explicit personalization features while ensuring that implicit personalization remains unobtrusive yet effective.

Given these results, system designers are encouraged to further optimize their algorithms such that relevant information is continuously supplied to users. A key issue we observe on ASNSs is that frequent users may encounter the same information for the times they visit a site. This might reduce their motivation to continuously use the site. Perhaps, the integration of other persuasive principles that direct frequent users' attention to other activities they could perform can increase engagement with the site. For example, frequent users who mostly access publications on a site may be engaged to share their views on topics under discussion for a reward.

6. Study Limitation

Though this study provides insightful revelations on how personalization approaches influence credibility perceptions, it has some limitations. To begin, the study is exploratory. Unlike an experimental research design, exploratory research may not provide adequate details of the causality of the relationship between the observed variables (in this case Implicit, Explicit personalization, and perceived credibility). Moreover, the respondents of this study are users of different ASNSs. This study admits that different ASNSs may have different features and interaction mechanisms which may have affected the results. Future studies could focus more on a particular ASNS, to verify the outcome of this study.

7. Conclusion and Future Work

The findings of this study provide relevant directions for building credible ASNSs. The results enhance our knowledge of the different personalization approaches and their importance in the design of ASNSs that are perceived to be credible. It directs system designers to prioritize Implicit personalization for increased credibility perceptions on ASNSs. Further, we extend the frontiers of IPMA and its relevance for comparing different phenomena. The findings and recommendations offered in this study do not only augment existing ASNS literature but extend to the broad arena of HCI research that focuses on system credibility.

The results from this study open a multitude of research opportunities for future studies. For instance, this study found Explicit personalization to be negatively correlated to perceived credibility. Several other reasons might have accounted for this. Therefore, further inquiry into why this result was recorded may be informative. For example, studies may investigate how the number of items on an explicit personalization list affects users' preferences and perceptions of the system. Moreover, further understanding of how user characteristics (such as age, gender, cultural background, or personality) affect preferences for personalization approaches will be needed. As indicated, future studies may investigate how personalizing the personalization approach, for example, based on certain user characteristics influences their attitude toward the system. Finally, we hope for both more cross-domain and experimental studies analysis on personalization to deepen our understanding of the concept.

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