Mohamed El-Bachir El-Ibrahimi University
Faculty of Mathematics and Computer Science
Department of Computer Science

Trust and Related Concepts in Social Networks

Laifa Meriem

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Committee :

Pr Boubetra Abdelhak	University of Bordj Bou Arreridj	Jury president
Pr Zarour Nacer Eddine	University of Constantine 2	Examiner
Dr. Zitouni Abdelhafid	University of Constantine 2	Examiner
Dr Nouioua Farid	University of Bordj Bou Arreridj	Examiner
Pr. Maamri Ramdane	University of Constantine 2	Supervisor
Dr. Akhrouf Samir	University of Bordj Bou Arreridj	Co-supervisor

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In memory of my father

To my family … To my mother

To my friends, colleagues and teachers

To my cheerleaders … To my readers

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Abstract

Online social networks (OSN) have become extensively used in people's everyday social activities where relationships are initiated, developed or ended. The move towards online communications shifted our social perspectives and behavior, which gave rise to several theories and many empirical studies assessing the differences between online and traditional offline interactions, and how they are affecting the ways people communicate. Trust is the heart of social life and the backbone of relationships. However, assuring the continuity of trust relationships in an online environment can be challenging. Forgiveness is one way to repair a wounded relationship. By bridging research on trust and forgiveness, we underline the necessity to inspect forgiveness in the digital context by contributing to the literature in three major ways. We first investigate if forgiveness can be predicted by the same factors that were proven to affect it in offline settings. We also hypothesize that users' acceptance and involvement in the used social network platform would have a significant impact on their forgiveness of an offense that takes place on that same tool. Second, we analyze whether the decrease of trust after an offense can be affected by the presence of forgiveness. The third contribution concerns the applicability of artificial intelligence techniques in predicting forgiveness and simulating its positive effect in maintaining relationships in a social network.

To achieve these goals, we collected data from over 300 participants who took part in this study by completing a questionnaire that recorded different measurements. Next, a two-staged approach was used, first to test the proposed research model using structural equation modeling (SEM), then the results were employed as inputs for artificial neural network (ANN) and fuzzy logic (FL) models. Unexpectedly, the severity of the offense, its frequency, pre-transgression trust and empathy were found to be the main factors that influence forgiveness, while commitment and apology had no significant direct effect. Moreover, analyzed data discarded the hypotheses that users' acceptance and involvement in the used social network platform have any significant effect on their forgiveness. Results also showed that a victim's trust towards the transgressor decreased much more in the absence of forgiveness than in its presence. On the other hand, combining ANN and FL was found to provide more accurate prediction results. Further, simulation experiments called attention to the prospective benefits of forgiveness in maintaining connectedness in a digital environment. Finally, the provided future work and implications of this thesis is believed to inspire

further research for a better understanding of both trust and forgiveness in social context in the digital age.

Keywords: Social Networks, Trust, Forgiveness, Trust Behavior, Trust Belief, Empathy, Commitment, Apology, Facebook, Structural Equation Modeling, Artificial Neural Networks, Fuzzy Logic, Simulation.

Résumé

Les réseaux sociaux en ligne (OSN) sont de plus en plus utilisés dans les activités sociales quotidiennes où des relations sont initiées, développées ou terminées. L'usage de l'internet pour les communications en ligne a changé nos perspectives et nos comportements sociaux, ce qui a donné naissance à plusieurs théories et a permis de réaliser de nombreuses études empiriques pour évaluer les différences entre les interactions en ligne et hors ligne et voir comment elles affectent la manière dont les personnes communiquent. Dans le monde réel, la confiance et le pardon sont considérés comme étant les piliers de la vie sociale et le pivot des relations. Néanmoins, vouloir assurer la continuité des relations de confiance dans un environnement en ligne et tout à fait différent et peut-être difficile à maintenir. Cependant on considère le pardon comme un moyen pour réparer une relation brisée. En mettant en relief et en reliant la recherche sur les notions de confiance et de pardon, nous soulignons la nécessité d'examiner le pardon dans le contexte numérique en contribuant à la prise en compte de ce concept dans la littérature de trois manières différentes. Nous étudions d'abord si le pardon peut être prédit dans le monde virtuel par les mêmes facteurs qui l'on prédit dans des paramètres du monde réel. Nous supposons également que l'acceptation et l'implication des utilisateurs dans la plate-forme du réseau social utilisé auront un impact important sur leur pardon lorsqu'un problème survient sur cet environnement. Deuxièmement, nous analysons si la diminution de la confiance après une dispute peut être affectée par la présence de la notion de pardon. La troisième contribution concerne l'applicabilité des techniques d'intelligence artificielle pour prédire le pardon et simuler son effet positif pour maintenir des relations dans un réseau social.

Pour atteindre ces objectifs, nous avons réalisé une étude pour recueillir des informations auprès de plus de 300 participants qui ont contribué à répondre à un questionnaire qui a permis de réaliser différentes mesures. Ensuite, une approche à deux étapes a été utilisée, premièrement pour tester le modèle de recherche proposé en utilisant la modélisation de l'équation structurale (SEM), puis les résultats ont été utilisés comme des données d'entrée pour un modèle de réseaux de neurones artificiels (ANN) et un modèle de logique floue (FL). De manière inattendue, la gravité de la transgression, sa fréquence, la confiance avant celle-ci et l'empathie ont été les principaux facteurs qui influent sur le pardon, alors que l'engagement et l'excuse n'ont pas d'effet significatif direct. En outre, les données analysées ont écarté les hypothèses selon lesquelles l'acceptation et l'implication des utilisateurs dans la plate-forme utilisée du réseau social ont un effet significatif sur leur pardon. Les résultats ont également montré que la confiance de la victime envers le transgresseur a beaucoup plus diminué en l'absence de pardon qu'en sa présence. D'autre part, la combinaison des techniques d'ANN et FL a permis de fournir des résultats de prédiction plus précis. De plus, les expériences de simulation ont attiré notre attention sur les avantages potentiels du pardon pour maintenir la connectivité dans un environnement numérique.

Mots-clés: Réseaux Sociaux, Confiance, Pardon, Comportement De Confiance, Croyance De Confiance, Empathie, Engagement, Excuse, Facebook, Modélisation d'équations Structurelles, Réseaux de Neurones Artificiels, Logique Floue, Simulation.

ملـخـص

أصبحت الشبكات الاجتماعية عبر الإنترنت تستخدم على نطاق واسع في الأنشطة الاجتماعية اليومية للأشخاص حيث يتم بدء العلاقات أو تطويرها أو إنهاؤها. التوجه نحو الاتصالات عبر الإنترنت غير من وجهات نظرنا الاجتماعية والسلوكية، مما أدى إلى انتاج العديد من النظريات والدراسات التجريبية لتقييم الاختلافات بين التفاعلات عبر الانترنت والتفاعلات التقليدية، وكيف أنها تؤثر على طرق تواصل الناس. الثقة هي قلب الحياة الاجتماعية والعمود الفقري للعلاقات. ومع ذلك، فإن ضمان استمرارية علاقات الثقة في بيئة الإنترنت يمكن أن يكون أمرا صعبا. العفو هو أحد الطرق لإصلاح العلاقة المتضررة. من خلال الربط بين البحوث حول الثقة والعفو، نؤكد في هذا العمل على ضرورة درس العفو في المجال الرقمي من خلال المساهمة بثلاث طرق رئيسية. أولا نتحرى إذا كان يمكن التنبؤ بالعفو عن طريق نفس العوامل التي ثبت أنها تؤثر عليه في دراسات سابقة في الاتصالات التقليدية. ونفترض أيضا أن قبول المستخدمين واشتراكهم في منصة الشبكة الاجتماعية المستخدمة سيكون له تأثير كبير على العفو لهم عن الاساءة التي تحدث على تلك الأداة نفسها. ثانيا، نحلل ما إذا كان انخفاض الثقة بعد الاساءة يمكن أن يتأثر بوجود العفو. تتعلق المساهمة الثالثة بتطبيق تقنيات الذكاء الاصطناعي في التنبؤ بالعفو ومحاكاة تأثيره الإيجابي في الحفاظ على العلاقات في الشبكة الاجتماعية.

لتحقيق هذه الأهداف، جمعنا بيانات من أكثر من 300 مشارك شاركوا في هذه الدراسة من خلال استكمال استبيان سجل قياسات مختلفة. بعد ذلك، تم أولا اختبار نموذج البحث المقترح باستخدام نماذج المعادلات البنائية، ثم استخدمت النتائج كمعطيات للشبكات العصبونية الاصطناعية ونماذج المنطق الضبابي. بشكل غير متوقع، وجد أن شدة الاساءة، تواترها، وثقة ما قبل الاعتداء والتعاطف هي العوامل الرئيسية التي تؤثر على العفو، في حين أن الالتزام والاعتذار ليس لهما تأثير مباشر كبير. علاوة على ذلك، البيانات التي تم تحليلها ألغت الفرضية القائلة بأن قبول المستخدمين ومشاركتهم في منصة الشبكة الاجتماعية المستخدمة يكون لها أي تأثير على العفو. وأظهرت النتائج أيضا أن ثقة الضحية تجاه المعتدي انخفضت أكثر بكثير في غياب العفو عنه في وجوده. من ناحية أخرى، تم العثور على أن الجمع بين الشبكات العصبونية الاصطناعية ونماذج المنطق الضبابي يوفر نتائج تنبؤ بالعفو أكثر دقة. من جهة أخرى، دعت تجارب المحاكاة للانتباه إلى الفوائد المتوقعة من العفو في الحفاظ على العلاقات في بيئة رقمية.

الكلمات المفتاحية: الشبكات الاجتماعية، الثقة، العفو، التعاطف، الالتزام، الاعتذار، الفاسبوك، نماذج المعادلة البنائية، الشبكات العصبية الاصطناعية، المنطق الضبابي، المحاكاة.

"Science, however, is never conducted as a popularity contest, but instead advances through testable, reproducible, and falsifiable theories."

Michio Kaku

"The important thing in science is not so much to obtain new facts as to discover new ways of thinking about them."

William Lawrence Bragg

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Chapter 1

Introduction

Humans have always had the inclination to communicate with each other over short and long distances. To satisfy this desire, people used many tools to connect and converse. These tools have changed significantly over time from unpretentious inception of smoke signals and blowing horns to developed writing systems and letters.

As people's drive to communicate with each other persisted and grew, new technologies emerged to facilitate communications despite lengthy mileage. The succeeding immense phase in communication tools development occurred in 1990 when Tim Berners-Lee[1]and Robert Cailliau[2] combined the internet and its Domain Name System (DNS) with the idea of hypertext which created the first World Wide Web (WWW) server. Once the web became available to the public, it grew very fast, extending to reach many fields such as the appearance of Amazon and lunching of Yahoo! and MSN in in 1995.

Even though the Internet has been around for a relatively short time, it became a tool of communication all over the world that people take for granted. One of the main factors that caused the widespread use of the Internet is the fast development and growth of new technologies (such as PCs and smartphones). Consequently, people's communication changed drastically. Instead of using telephones, it became prevalent to converse through emails, instant messaging, and many

[1] https://www.w3.org/People/Berners-Lee/

[2] https://www.cailliau.org/

other web-based services. The most recent tendency in online communication is *online social networks* (OSN). They have become a significant part of our modern civilization by giving a scope to everyone to express and share ideas, feelings and business. The widespread use of different social network platforms (for personal or professional purposes) raised our awareness of the world in which we are living. For example, **Twitter** spread news quickly, and make them more available and accessible. **Facebook** and **Google+** broke down the time and space constraints in our daily social interactions. Companies are creating closer connections with their customers through **Instagram**.

The shift towards online communications gave rise to several theories and many empirical studies assessing the differences between online and traditional offline interactions and how the Internet is affecting the ways people communicate with each other. These studies focused mainly on the verbal and temporal (asynchronous) qualities of online communications where nonverbal cues (such as self-presentation, voice, emotions and physical appearance) are usually absent. The majority of these studies anticipated that the absence of nonverbal cues in online communications suppressed the interpersonal touch. However, social *information processing theory* proposed by Walther [1] contradicted this claim and suggested that "communicators adapt to the channel capacity of communication media". According to this theory, online communications and interactions can be as effective as face-to-face ones as long as people are motivated to engage in social relationships, but the required time to process the shared information is longer. The rest of this thesis is built based on the premises that offline communication theories can be applied in online settings.

1.1 Motivation

The wide adoption and use of recent technologies and innovations, such as social media, have transformed our capabilities to perform more complicated tasks and shifted our social perspectives and behavior. Integrating these technologies in varied aspects had - and continues to have – a noteworthy impact on societies in different forms. For instance, Facebook became widely used in people's everyday social activities where communities are emerging online, and relationships are initiated, developed and/or ended. Despite the fact that the digital age's effect on interpersonal relationships is still growing [2]–[4] and the structure and standards of such relationships are evolving, societies are urged to redefine the actions that are publicly applicable and suitable in digital settings. At the heart of the online social space, trust is considered to play a key role in bolstering successful interactions, which attracted many researchers. However, in online communications, relationships sometimes go amiss because of an upsetting or hurtful deed even from those we trust the most. On the other hand, and regardless of the positive impacts of social media, there are a number of ways in which they can be used to cause more harm than good [5]. People can easily be offended or hurt on social media due to privacy matters or cyberbullying, which can cause health issues (such as stress and anxiety) or lead to suicide - in some cases [6].

While trust between individuals is argued to help resolve conflicts [7], forgiveness is believed to play a key role in repairing interpersonal relationships after a transgression [8], [9]. Studies have shown that forgiveness is important and beneficial in many ways. For example, forgiveness usually reduces anger, sadness and negative emotions[10]. It also sustains healthy relationships and repair broken trust relations. In addition, forgiveness can improve health by lowering blood pressure, stress and depression risks, and rising spiritual and psychological well-being[10]. On the other hand, forgiving may improve connectedness and cooperation within the community by increasing empathy, tolerance and understanding between community members, as well as reducing guilt and reinforcing solutions for conflicts[10]–[13]. These benefits affect both sides: the forgiver and the forgiven. Subsequently, we believe that introducing forgiveness to a digital environment, more precisely to online social networks can have the same beneficial effects on enhancing users' experiences.

Whereas scholars across a variety of disciplines have studied trust in online settings, much less attention has been paid to forgiveness. Nevertheless, many of those who study forgiveness relate it to forgetting, claiming that forgiveness benefits cannot be fully exploited in the digital age when the reminder of the transgression is still present [14]. However, in this study we focus on the most common conception of interpersonal forgiveness instead of forgetting.

In this thesis, we contributed to some of the most fresh and exciting developments in this still thriving domain, namely the potential of trust and forgiveness for maintaining online relationships and connectedness. By bridging research on trust and forgiveness, we emphasize the need to examine forgiveness in the context in which the conflict occurs and we contribute to the literature in three main ways. First, as there is a lack of studies about forgiveness in the digital age, our research builds upon existing studies to examine if forgiveness can be predicted by the same factors that were proven to affect it in offline settings. In addition, we investigate whether victims' acceptance and involvement in the used social network have a significant impact on their decision to forgive an offense that takes place on that social network. Second, we inspect if the decrease of trust after and offense can be affected by the presence of forgiveness. Third, we rely on artificial intelligence techniques to implement the resulting forgiveness model and then to simulate its benefits in a social network. We believe that this study will inspire further research for a better understanding of both trust and forgiveness in a social context in the digital age.

1.2 Relevance to Computer science

Much of this thesis is about sociological and psychological concepts such as trust, forgiveness, and empathy. These concepts relate to a contemporary computer science field known as *social computing*. Social computing is the combination of computer science and social sciences that weaves computational tools and social behavior and interactions theories. As argued earlier, the emergence of new technologies and online communities opens new perceptions of interactions and behaviors. On social networks for instance, face-to-face interactions and physical cues no longer apply. Consequently, new paradigms are needed.

In our research project, we are specifically interested in trust and forgiveness in a digital context. We believe that such social concepts have significant roles for enhancing online users' experience. There has been an extensive work for modeling trust in computer science (see **Section 2.1.4**). However, less attention is paid to forgiveness, where only few studies can be found in computer science field that tackle its benefits. This thesis attempts to build on existing diverse sources from the literature to provide a new perspective of the relationship between different concepts, and a computational model for predicting forgiveness in a digital context.

On the other hand, researchers in artificial intelligence have adopted heavily from sociological and psychological fields in modeling sociological concepts in general and trust and forgiveness specifically [9], [15]–[20]. Therefore, we believe that there exist many opportunities to explore in this path, and that artificial intelligence techniques will provide a deeper understanding of these concepts in the digital environment.

1.3 Research settings and data collection

In order to attain our research goals, two main approaches were employed: a statistical approach followed by Soft computing techniques. As there is no available and appropriate data that fit our research purposes, two surveys were conducted in order to investigate our research questions and hypotheses and to collect suitable data for training and testing phases. Both started with an *Anonymous Survey Consent* that can be found in **Appendix A**. A survey technique was chosen for the following reasons:

- ✓ **Anonymity:** self-administrated questionnaires ensure privacy for participants, which make them less intimidated and more honest in their responses.
- ✓ **Cost:** Online surveys – in particular – are relatively inexpensive and affordable for most researchers.
- ✓ **Large coverage:** surveys are useful in describing the characteristics of a large population. They can provide a high level of general capability in representing a large population that cannot be observed directly.
- ✓ **Flexibility:** different administration modes and various languages can be used for the same study and with the same population.
- ✓ **Popularity:** surveys are a popular method for quantitative and descriptive research in different fields of science that aim to describe natural occurring behaviors in the real world. This can allow comparative analysis between diverse studies.
- ✓ **Efficiency and effectiveness:** surveys provide a snapshot of behaviors and attitudes about the target population by measuring a wide variety of unobservable constructs and collect information on a broad range of things (e.g.; personality traits, opinions, past behaviors, etc.).

The first survey contained open questions and was conducted to investigate users' trusting behaviors with their Facebook friends and acts that deem offensive so as to create appropriate items and scenarios in the second survey. It also contained other open questions that will be addressed later on in the thesis. All items of the first survey can be found in **Appendix B**. The second survey was used to collect the needed data in order to test the research model. Based on participants' responses and comments from the first survey, the second survey was designed using a 2 (hypothetical offense) × 2 (apology: yes vs no) × 2 (frequency: once vs many times) experimental design, in which participants imagined themselves as the victims of an offense (see **Appendix C**). Both surveys were translated to Arabic, as it is the official Algerian language. Respondents could complete the survey anonymously online - using *Qualtrics* - in their language of choice (either English or Arabic).

For both surveys, only participants who are Facebook users were invited to take part in the study. 100 students from the university of Bordj Bou Arreridj in Algeria were invited to participate in the first survey. 83 complete responses were received (53% female). After analyzing those responses, the second survey was drafted and its items reviewed by an expert and tested with colleagues. Then, an invitation for participation along with the final version of the survey were sent to 608 students from the same university, from February to the end of March of 2016. A total of 400 responses were received (response rate = 65.57%), where 323 valid and complete responses (with a completion rate of 80.75%) were subject to analysis. Respondents of both surveys did not receive any compensation (monetary or other). The surveys started with an explanation of their purpose, confidentiality, and how long it will take (10 to 15 minutes). Demographic questions were asked first, including age, gender, level of education, marital status, and the language they use the most in their online communications. Demographic information about respondents of both surveys is shown in **Figures 1,2,3** and **4**.

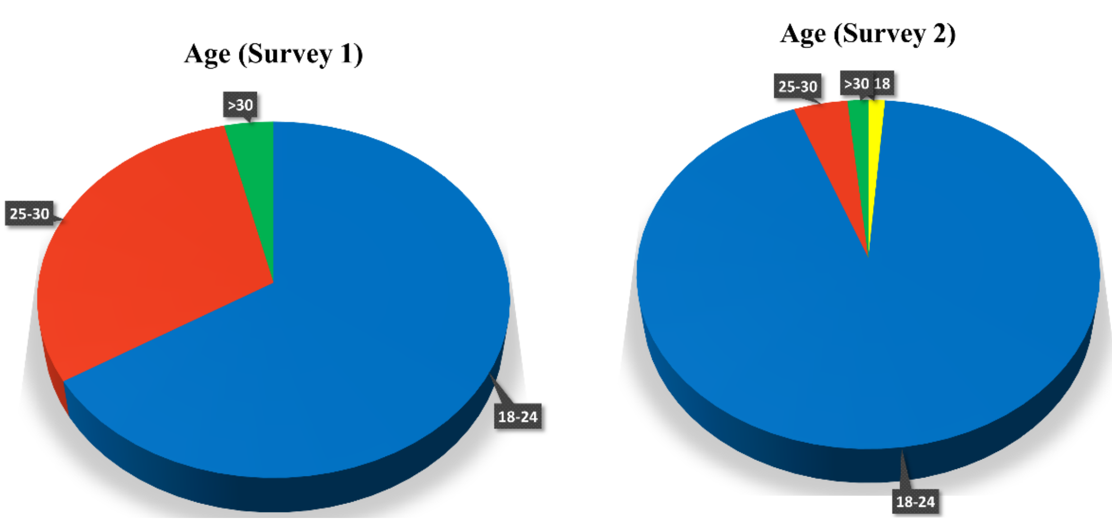

Figure 1. *Respondents' age*

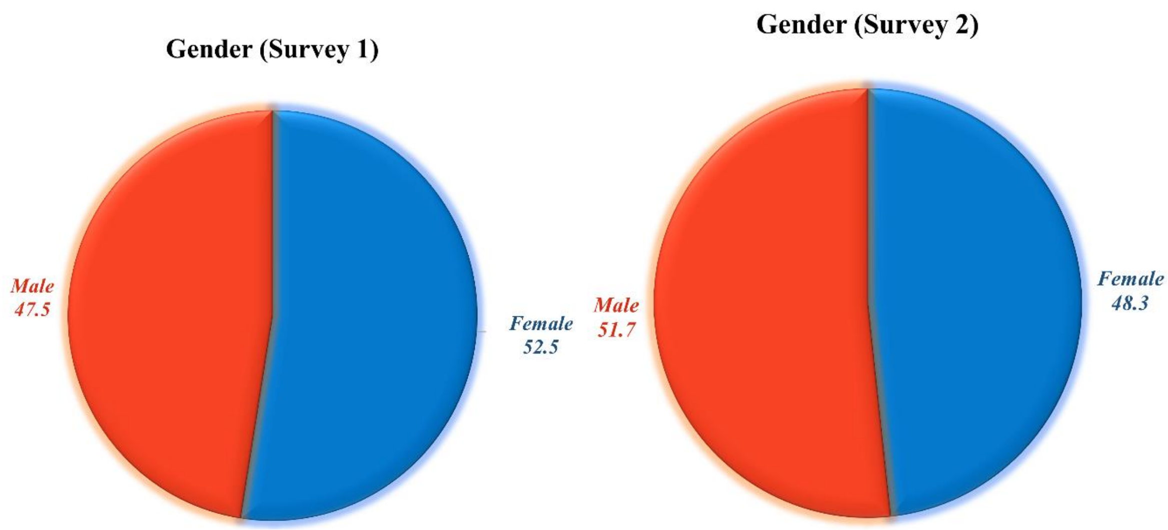

Figure 2. *Respondents' gender*

According to a recent report by the Internet World Stats [21], the number of Algerian users of Facebook was about 15,000,000 in June 2016. Therefore, a sample size of 323 cases was found adequate to represent Algerian Facebook users, with a confidence level of 95% and confidence interval of ±5.45%.

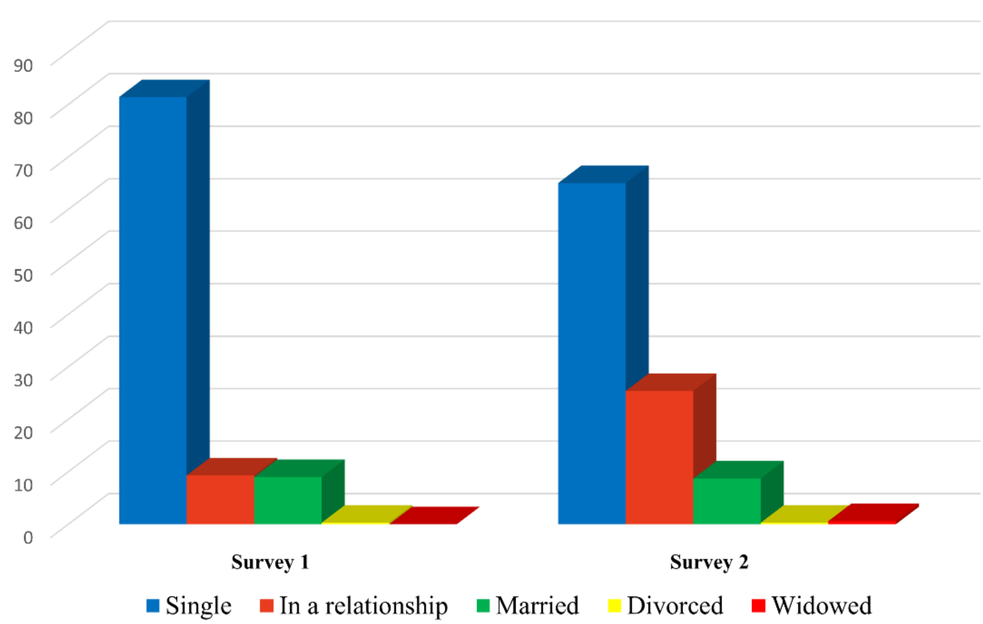

Figure 3. *Respondents' marital status*

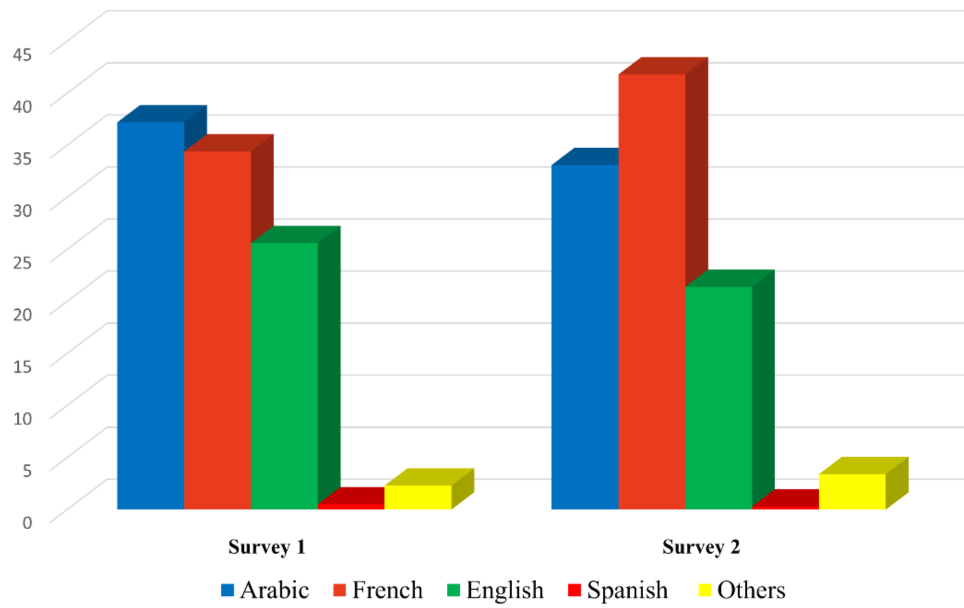

Figure 4. *Used language in online communications*

Prior to analysis, measurement validation was assessed to assure that the research methods and collected data in the analysis step are reliable and valid. The research procedure is shown in **Figure 5**. The validity of the proposed research model was then tested using a Structural Equation Modeling (SEM) approach, which is widely used in different recent studies. Many studies argue that 150 to 200 subjects is the minimum satisfactory sample size to obtain reliable results in SEM [22], [23]. The sample size of our second survey is 323, which meets the requirement.

1.4 Outline and primary contributions

This dissertation is organized in six chapters. In the following, we summarize these chapters along the dissertation main contributions:

Chapter 1 includes an introduction to the context of our work, in addition to the research settings and data collection process that we used.

In **Chapter 2,** we introduce the two main concepts that will be encountered throughout the rest of the dissertation: trust and forgiveness. An overview of online trust is provided by focusing on its social aspect, its properties and its metrics. We also provide a classification of the existing related work to this concept. Next, we present an overview about forgiveness research in the digital environment to put the first basic stones of our work and familiarize the reader with the context of our work.

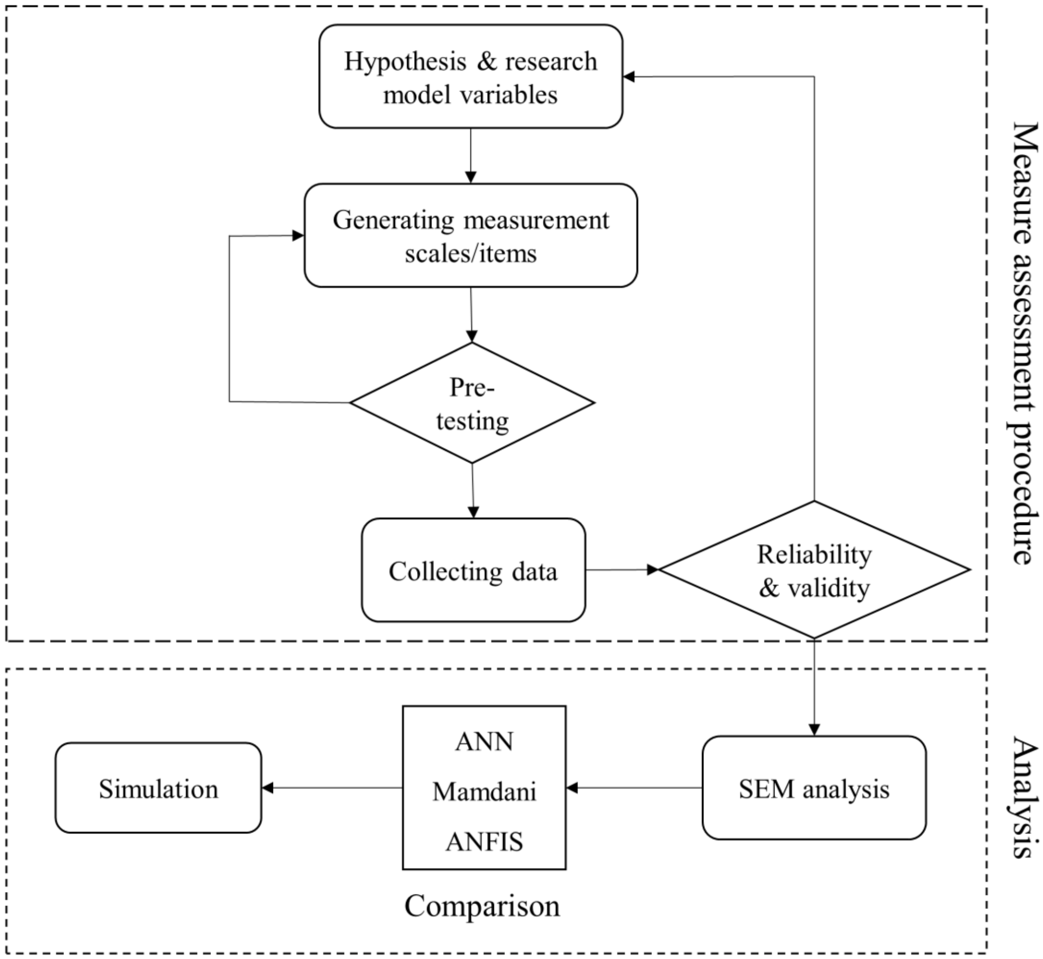

Figure 5. *Research and data collection procedure*

In **Chapter 3**, we focus on Facebook as it is the chosen platform for our research. We aim in this chapter mainly to investigate Facebook usage purposes by Algerian students, as well as their acceptance and involvement in using it. The study also examines the relationship between Involvement in Facebook and acceptance. The analysis builds upon previous investigations but focuses on Algerian students, as they are the participants of this study.

In **Chapter 4**, we condense into examining different factors that can affect forgiveness decision of a victim of an online offense and in a social network context. Drawing upon the existing literature about forgiveness in offline settings, we primarily proposed a research model and empirically tested it through the survey. In addition, we inspect trust dynamics and whether the decrease of trust after an online-related offense can be affected by forgiveness. To operationalize the theory, a concrete model is needed, where ranges and weights of all the factors as well as the way they affect victims' decisions are defined. To this end, the significant variables will be used as inputs to develop forgiveness prediction models in the following chapter.

In **Chapter 5**, we show a possible implementation of the theoretical forgiveness model developed in the previous chapter. This implementation uses a neural network and a fuzzy approaches. In particular our attempt is to evaluate, using a specific implementation, the applicability of soft computing techniques in predicting forgiveness. Subsequently, simulation experiments were carried out using previously developed model, to call attention to the potential benefits of forgiveness in maintaining connectedness in a social network.

Finally, **Chapter 6** presents a general conclusion, where we summarize and evaluate the achieved goals of this research. We also address some challenges we faced during conducting different studies, and discuss some possible extensions of the current work and we propose future work that can overcome these challenges and limitations. Some theoretical and practical implications are also provided in this chapter as well.

Chapter 2
Background[3]

In this chapter, we focus on two main concepts: trust and forgiveness. The concept of trust is widely used in computer science in various contexts and for different aims. This variety can confuse or mislead our readers who are interested in trust concept but not familiar enough with it. Therefore, we give in this chapter an overview of online trust by focusing on its social aspect, its properties and its metrics. We also provide a classification of the existing related work to this concept. Next, we present an overview about forgiveness research in the digital environment to put the first basic stones of our work.

2.1 Trust

2.1.1 Definitions

Trust relationship involves two parties: a trustor (the one who expresses trust on the other party) and a trustee (the trusted party), and they both interact through available combination of social and technical means. For generality purposes, we consider the trustor and the trustee to be agents that can represent persons, computers or artificial agents.

[3] Parts of this chapter have appeared in the following conference papers:

- Laifa, M., Akrouf, S., & Maamri, R. (2015, November). Online Social Trust: an Overview. In Proceedings of the International Conference on Intelligent Information Processing, Security and Advanced Communication (p. 9). ACM.
- Laifa, M., Akrouf, S., & Maamri, R. (2015, November). An Overview of Forgiveness in The Digital Environment. In Proceedings of the International Conference on Intelligent Information Processing, Security and Advanced Communication (p. 38). ACM.

In a simple sense, trust means confidence, reliability, competence, integrity, credibility, belief and faith. In a more complex and deep sense, trust is an interdisciplinary concept with several meanings [24]. Thus, providing a general and simple definition of trust is a strenuous task. Before we discuss its definitions in computer science, we address the psychological and sociological view of trust concept.

In psychology, trust definition is broadly built on three aspects: *cognitive* (based on reason and rational behavior), *emotional* (based on the security and comfort) and *behavioral* (based on the trustee's behavior) [24]. Accordingly, trust is a psychological state of the trustor under dependence and vulnerability to the trustee, where the trustor is positively convinced about the trustee's intentions and capabilities, and expects that the trustee will behave in the trustor best interests [25], [26].

In sociology, trust is defined as the willingness of a trustor to be vulnerable and dependent to the trustee based on an optimistic bet or expectation about the future uncertain behavior and decisions of the trustee in a context where that expectation has an influence upon the action or decision of the trustor [27]. At the individual aspect, this definition is similar to the psychological view of trust. Whereas, at the social level, trust is a *collective* psychological state of the group implies that members of a social group act according to the expectation that other members of the group are trustworthy [28].

In computer science, the notion of trust is derived from sociology and psychology. There exist many definitions of trust due to the diversity of contexts. In a security environment, Olmedilla, Rana, Matthews, and Nejdl [29] defined trust as a measurable belief of the trustor in that the trustee behaves dependably for a specified period within a specified context. Mui, Mohtashemi, and Halberstadt [30] defined trust in a reputation context - based on feedbacks on past interactions - as *"a subjective expectation an agent has about another's future behavior based on the history of their encounters"*. Whereas in internet applications context, Grandison and Sloman [31] consider the competence of agents not their previous actions. Thus, they defined trust as *"the firm belief in the competence of an agent to act dependably, securely and reliably within a specified context "*.

In agent systems environment, trust is defined as follows [9]: *"The belief (or a measure of it) that the trustee will act in the best interests of the trustor in a given situation, even when controls are unavailable and it may not be in the trustee's best interests to do so"*.

2.1.2 Trust properties

Because of the variety of trust meanings, many properties exist in the literature. In this section, we explain briefly the most notable properties in an online social context.

Context specific: trust values between the same agents can differ depending on the context of that trust relationship [25], [26] . For example: agent *a* trusts agent *b* in an e-commerce context but it does not trust it for a health advice. However, there is a lack of trust models in computer science that tackle the problem of how a trust model can be transferred from one context to another.

Subjectivity: trust is a personal opinion. As illustrated in **Figure 6** (a), agent *a* can trust agent *b* (black link) in specific settings, but agent *c* may not trust agent *b* (red link) in the same settings. Personal preferences of the trustor affect directly the computed trust value. Therefore, many models consider the personalization of trust like [30], [32], [33].

Asymmetry: this property is a special case of subjectivity: trust is not necessarily identical in both directions of a trust relationship due to differences in beliefs, expectations, situations, and other reasons [28], [32]. In our example (**Figure 6** (b)), agent *a* trusts agent *b* but this latter does not trust *a*.

Self-reinforcing: trust influences trust [34]: if *a* trusts *b*, it is likely it will act positively with it, which may create more trust between them in future interactions. Moreover, if *a* does not trust *b* (to some level), then it is unlikely that they will interact with each other, leading to unincreased trust between them.

Propagation: in a social environment, trust information can pass from an agent to another, thus trust is propagative [35], [36]. This does not make trust transitive: if *a* trusts *b*, and *b* trusts *c*, this does not imply that *a* trusts *c* for sure, but there is trust information that is likely to pass. The propagation nature of trust in a network of agents allows composing (aggregating) trust values between any two agents not directly connected or do not know each other. This property provides a good way to compute trust in computer science, especially in social networks [32], [37]. Taking an example in **Figure 6** (c), trust value between agents *a* and *e* can be predicted even though the two agents are not directly connected. The same goes for ($a \rightarrow f$) and ($d \rightarrow b$).

Dynamicity: trust evolves and decays with time and experiences. It is a very sensitive concept: one single event can destroy the trust we built in a long time. Distance between agents (from a network perspective) can decrease trust: the farther the trustor is from the trustee, the more trust value diminishes. Trust dynamic is widely modeled in computer science using different strategies like computing trust values periodically [38], considering only the most recent interactions [39] or choosing a temporal window of interactions [40].

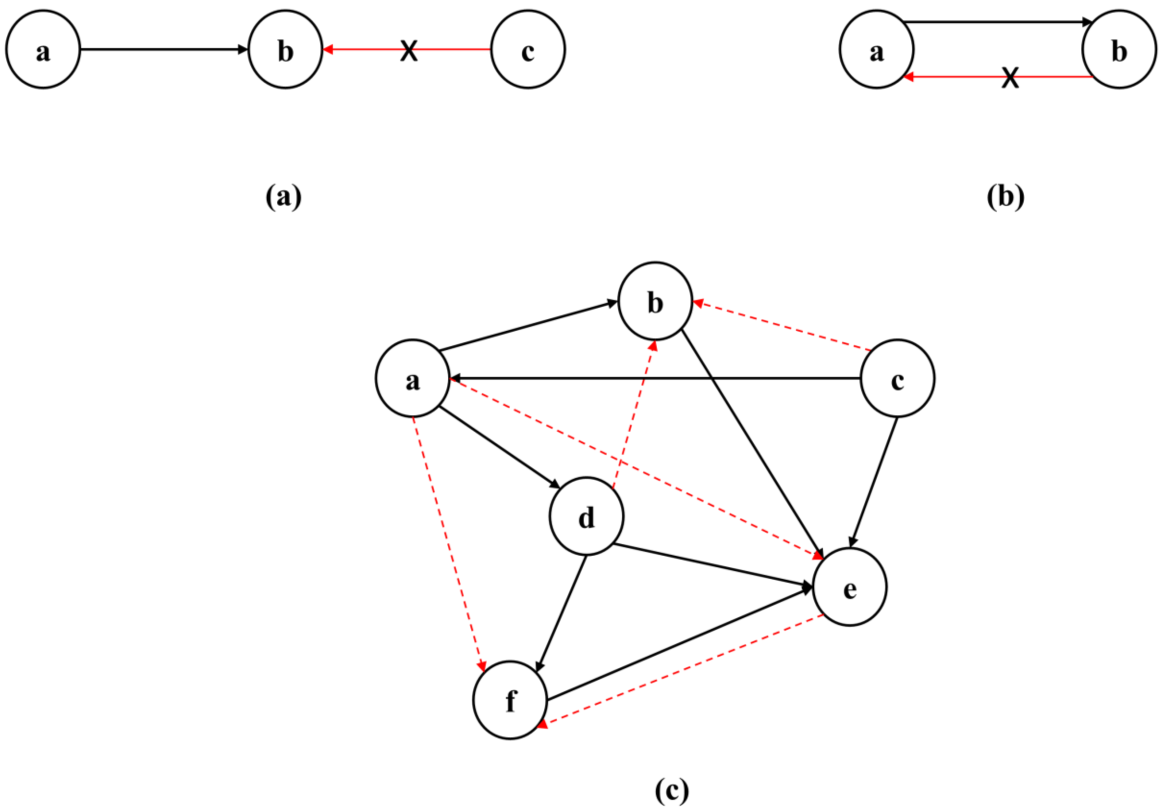

Figure 6. *Trust properties examples*

2.1.3 Trust metrics

In this context, the word metric is not the traditional mathematical distance between elements in a metric space. Trust metrics are techniques that compute quantitative estimates of trust between agents based on existing trust links in the trust network [37]. Several types of trust metrics exist in the literature. Ziegler [36] classified these metrics in different categories (see **Figure 7**). We briefly explain different trust metrics categories and refer to [36] for more details.

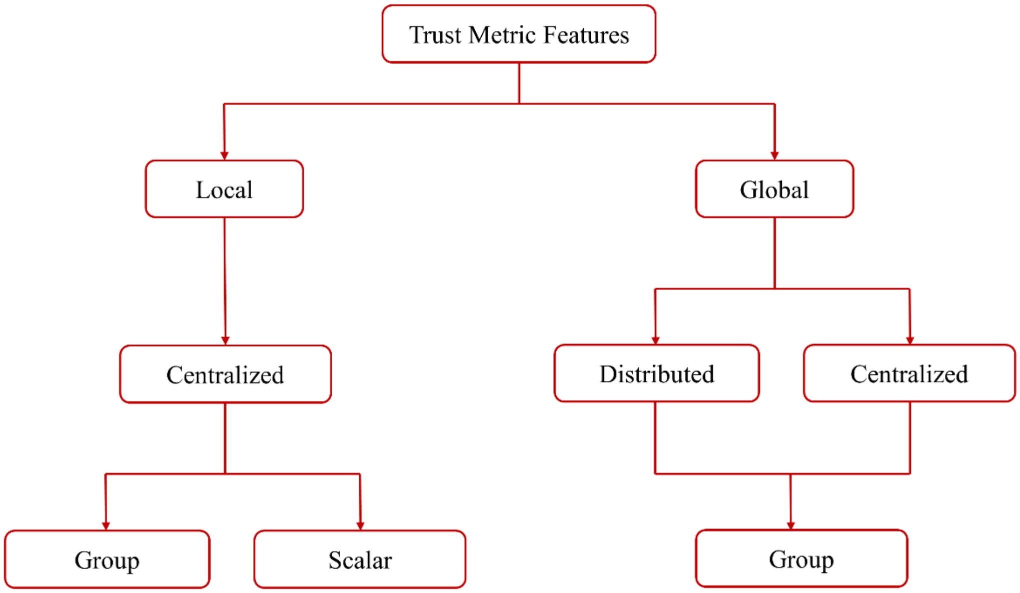

Figure 7. *Trust metrics classification [36]*

2.1.3.1. Local and global metrics

In this category, the network perspective is taken into consideration. Global approaches compute new trust values based on the complete trust graph (including all nodes and trust links) [41], [42]. This approach computes the global trust, which is more suitable for rating and reputation systems. On the other hand, local trust metrics investigate personalized trust between two nodes *a* and *b* by considering a partial trust graph information that contains all direct and indirect trust relationships emerged from *a* to *b* and the nodes within reach through these relationships. These metrics can be found in many studies such as [32], [37], [43], [44] to name a few.

2.1.3.2. Centralized and Distributed Metrics

The second trust metrics category takes into account the place of trust computation and quantification perspective. Centralized approaches perform all assessments in one machine [41], [45]. However, the data can be distributed. These approaches are more suitable for the semantic web because they consider only trust paths from the source node *a* to the target node *b*, and employ the 6 degrees of separation concept to minimize the CPU power required for computing.

Distributed metrics, on the other side, diffuse the computation on all nodes in the trust network [46]. These approaches are more used in peer-to-peer networks.

2.1.3.3. Group and Scalar Metrics

The perspective of the third category is about the way trust relationships are evaluated. In general, scalar metrics evaluate trust values between two nodes *a* and *b* in a group *G*, while group metrics compute trust for groups of nodes in *G*. Scalar trust metrics are naturally local [47], whereas group trust approaches can be either local or global [48], [49].

2.1.4 Trust research classification

Researchers introduced trust; a very familiar concept to humans, to control the overwhelming amount of information we are exposed to from social and technical environment. In the literature, there are several reviews that addressed different trust aspects and research areas (e.g. [28], [31], [50]–[53]). In the following, we focus on the social aspect of online trust, and we classify the reviewed work into three main categories as shown in **Figure 8**.

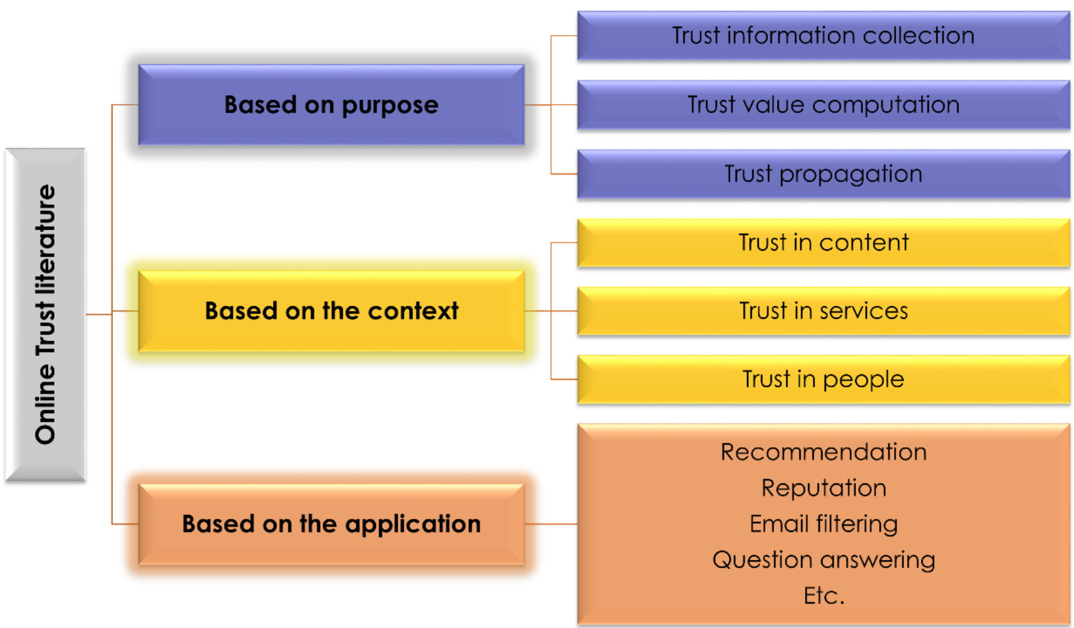

Figure 8. *Social trust related work classification*

2.1.4.1. Based on Purpose/Dimension

According to Sherchan and her colleagues [28], social trust literature can be divided into three groups based on the research purpose and trust dimension, as follows:

Trust Information Collection

Social trust information can be collected from three main sources. In economics, Dohmen, Falk, Huffman, and Sunde [54] proved that positive or negative *attitudes* toward an item are transmitted from parents to their children, which is considered to be a source of generalized trust. On the other hand, explicit users *experiences* (like feedbacks) and implicit (like changes in users interactions) are the major source of trust information in reputation based trust management models [40]. However, some researchers rely on consumers' *behavior* to build their reputation model [55]. In addition, Adali and his colleagues [56] detected trust-like behaviors to develop a quantitative measure of who trusts whom in Twitter network. These three trust information sources have been treated separately. Thus, combining different sources for the same trust model is an interesting future research.

Trust Value Computation

The second substantial trust research dimension is evaluating trust. Researchers have focused on two main groups of models: *graph-based* [57]–[59] and *interaction-based* models [60], [61]. Graph-based models are based on the network structure; how people are connected and how trust flows through it, whereas interaction-based models infer trust values only from users' interactions and behavior in the network. However, Trifunovic, Legendre, and Anastasiades [62] evaluated different forms of trust using both interactions and social network structure. Hybrid models are not well addressed in the literature, which can also be a promising future research area.

Trust Propagation

Trust propagation is about predicting the trustworthiness of any node in the network. According to [28], trust spreads in social networks by *recommendations* and/or *visualization*. For example, to deal with trust propagation predictions, Hang and Singh [59] proposed a trust-based recommendation approach to recommend trustworthy agents by considering the network structure (in-degree and friends-of-friends) and the trust values associated with links between agents. Peng and his colleagues [63] proposed a tool that helps users visually analyze trust relations to identify attacks and monitor trust evaluation. Trust-recommendation models are still more accurate and personalized, which denotes that more attention should be given to visualizing trust in social network.

2.1.4.2. Based on Context

Another criterion for classifying social trust research is the trusted context. Golbeck [53] divided her social trust survey based on this criterion as follows.

Trust in Content

The first group of research is concerned about which information should be trusted on the web. In e-commerce, trust between vendors and consumers is influenced by the website graphic and structure design, its content, products brand and presentation, interface properties, navigation fulfillment and social-cue design [64], [65]. Moreover, medical advice is critical information that became freely available on the web. Sillence and colleagues [66] proved that decisions to trust or reject this information are influenced by visual appeal, credibility and personalization of information content. Information provenance and sources provide farther insights on trustworthiness, like who created the original information, and whether it was manipulated before sharing [67].

Trust in Services

In the e-commerce context, the quality of the service, competence of merchants and reliability and environment security are the main factors that impact customers' trust and satisfaction, which directly influence customers' loyalty to the service and intentions to buy or invest online [68]–[70]. In the e-government context, trust plays an important role in helping citizens controlling risk, securely sharing personal information, and making online government transaction. Alsaghier, Ford, Nguyen, and Hexel [71] proposed a conceptual model of citizens' trust in e-government using Q-methodology to ensure the model's constructs validity and reliability.

Furthermore, trust is a big challenge for cloud technology due to resources limitation. Manuel [72] proposed a trust management system that combines quality of service requirements of users and capabilities of cloud resource provider. Kim and colleagues [73] also presented a trust model to provide highly trusted resources and best services to users based on collected historical information on resources reliability.

Trust in People

Social networks are based on users' communications. Due to the complicated nature of human-to-human interaction, researchers employed social trust models to encourage engagement amongst members of online communities in many manners. One way is recommending whom to connect to or follow next. Agarwal and Bharadwaj [74] used a real-valued genetic algorithm to learn users preferences based on their profiles attributes then employed trust propagation techniques to relieve collaborative filtering sparsity problem. STrust [75] is another social behavior-based trust model for friends' recommendation. It considers different users behaviors in a variety of contexts, and distinguishes between passive and active ones. Moreover, Yang, Steck, and Liu [76] claim that some people tend to connect with a subset of friends instead of individual friends. They developed a circle-based recommender system that infers category-specific trust circles from rating data combined with social network data regarding different categories (videos, books, music, cars, etc.).

Another advantageous application of social trust models is predicting ties labels in a network. DuBois, Golbeck, and Srinivasan [77] presented a method for predicting trust and distrust (considered to be a negative trust) between users in a social network by combining a path-probability trust inference algorithm with a modified spring-embedded algorithm to infer network distance.

Furthermore, trust is an important factor to secure users networks. STor (a social network based on Tor[4]) integrated two main elements to achieve a secure anonymity: determining trust relationships between friends, and propagating trust over an anonymity network [78].

2.1.4.3. Based on Application

trust literature can also be ordered based on the application domain for which it is useful, like recommendation [37], [59], [74]–[76], [79], [80], reputation [30], [33], [81], web syndication [82], peer-to-peer systems [38], [40], negotiation [83], [84], healthcare [66], filtering [85], question answering [86], multi-agent systems[9], [33], [87], [88]. One should keep in mind that trust models can be applied to different application domains.

2.2 Forgiveness

2.2.1 Definition

In philosophy, forgiveness is seen as a moral virtue between two individuals; an *offender* who committed a wrong deed to a *victim*, and they should be capable of communicating with each other

[4] https://www.torproject.org/

[8]. Forgiveness implicates overcoming inner negative feelings caused by the offense, like anger, resentment and desire of revenge, without forgetting the wrong deed that was done [8].

Nonetheless, social psychology is wealthy of definitions due to the multiplicity of studies on forgiveness. Berecz [89] saw forgiveness as “letting go of past hurt and bitterness”. Other researchers consider forgiveness to be the victim’s cancelation of a debt, even though he/she deserves repayment [90]. However, most psychologists define interpersonal forgiveness as a set of prosocial motivational changes that occur after an offense, and it involves decreasing negative affect and/or behaviors and increasing positive ones, towards an offender who does not necessarily deserve these changes [91], [92]. Positive motivations are increased by “reconciliation and goodwill for the offender” [20]. As we are focusing on repairing and restoring broken trust relationships, we adopt Rusbult [12] definition for interpersonal forgiveness, that is: “the victim’s willingness to resume pre-transgression interaction tendencies—the willingness to forego grudge and vengeance, instead coming to behave toward the perpetrator in a positive and constructive manner”.

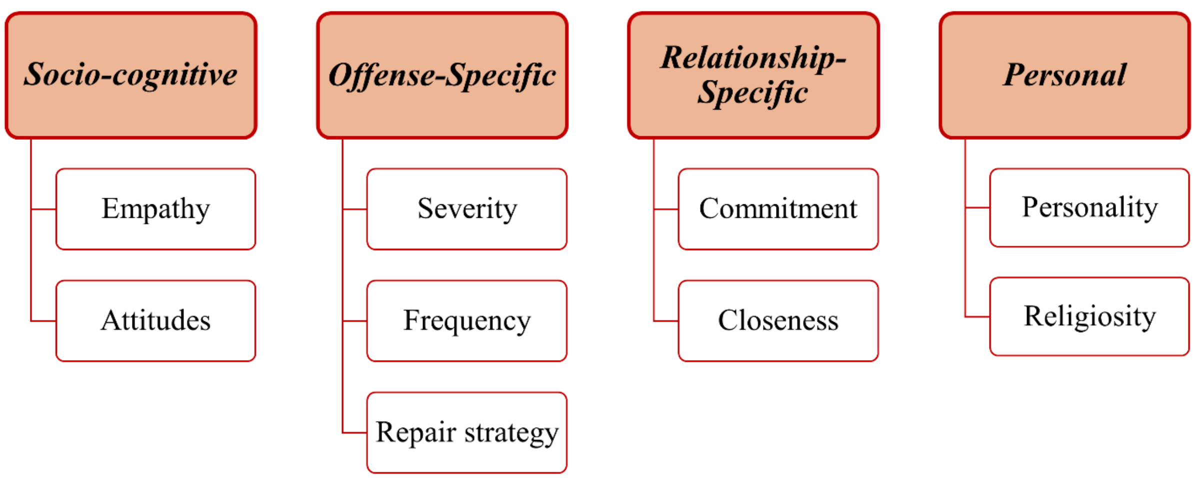

Figure 9. *Forgiveness Factors categorization*

2.2.2 Forgiveness factors/predictors

Forgiveness is a complicated decision that depends on many factors (also called predictors), which affect it directly or indirectly. From psychology literature, these factors are divided into four main categories that are presented below along with the most important predictors. **Figure 9** illustrates a summary of these predictors.

Social-Cognitive Factors

This category includes the most influential factors that involve the victim's interpretation of the offense [10], [92]. The most important social-cognitive factors are *empathy* (perceiving an event from the offender's perception, cognitively and emotionally) and *attribution* (cognitively ascribing the wrong deed to the offender). A high level of forgiveness was proven to correlate positively with empathy and positive attributions towards the offender [93]–[95].

Offense-Specific Factors

The second set of influential factors on forgiveness is related to the transgression itself. The victim's decision to forgive depends on the *severity* (perceived magnitude of a transgression's consequences) and *frequency* (discrete or chronic) of the transgression [92], [96], [97]. The more severe the transgression is, the harder it is to forgive it. In addition, a victim finds it more difficult to forgive an offender who commits the same offense repeatedly. Moreover, an offender may offer a repairing strategy (e.g. removing the offense, recompensing the victim, apology) for the harm he/she committed. Studies show that repairing strategies reduce the victim's anger and aggression towards the offender, and facilitate forgiveness [92], [96].

Relationship-Specific Factors

The pre-transgression relationship characteristics between the victim and the offender also have an impact on forgiveness. Finkel and his colleagues [98] found that victims who are strongly committed to the relationship are more likely to forgive their offenders. In addition to this, people tend to forgive wrongdoers who are closer to them (e.g. family member, close friend, a partner) than acquaintances and strangers [98], [99].

Personal Factors

The last category of factors that influence a forgiveness decision includes personality traits of the victim, which creates a predisposition to forgive or not. For example, victims with high agreeableness are more likely to forgive while those with high level of neuroticism tend to be less forgiving [10], [92], [100]. On the other hand, there is an argument about religiosity that effects forgiveness decision. While some studies argue that increased religiosity positively affects forgiveness [10], [100], other experiments show that its impact is only on how an individual feels about forgiveness itself but not on how much one tends to forgive [101]. Personal factors are considered to be the less influential on forgiveness decision [10], [96].

2.2.3 Forgiveness related work

The variety of forgiveness factors discloses the complexity of interpersonal forgiveness, which attracted many researchers to study its process and analyze its consequences. While scholars in many fields have studied interpersonal forgiveness and its benefits, forgiveness in online environment has not been explored in a great depth yet. In this section, we review existing work on forgiveness in the computer science and we divide it into three groups, based on the way forgiveness was perceived. **Table 1** summarizes the reviewed work. We included in our review only references where forgiveness was introduced *explicitly*.

2.2.3.1. Forgiveness as forgetting

While researchers in philosophy and social psychology have clearly separated forgiving from forgetting, we found that some other researchers relate these two concepts in the digital age arguing that we cannot fully exploit forgiveness and its social benefits if we cannot forget the reminders of the offense or violation [14]. Based on the same perception, Bishop and his colleagues [102] discussed forgiveness strong relation to forgetting the offense itself, and they explored five approaches to forget the wrong deed from the internet , these are:

(1) *controlling information diffusion* through revoking access by using access control models or cryptographic approaches or by deleting the information,
(2) *fooling the web* by providing a large amount of deceptive information,
(3) *misleading users* by attributing the information to someone else,
(4) *changing the semantics* of the information, or
(5) *combining* the inconvenient information with other data to take advantage of it.

Reputation defender[5], for instance, is a reputation management company that provide services to individuals and businesses to improve and defend their online reputation. The company's products and services are designed based on some of these cited approaches.

Even though these approaches can be effective, they also rise some non-technical and technical questions. For example, how can these approaches be efficient when the offender (the inconvenient information provider) does not own that offending information and its access? How

[5] www.reputation.com

can a system be designed that takes into account legal and cultural differences? On the other hand, the same approaches can be used to cause harm, then how can system designers prevent it?

Table 1. *Summary of reviewed existing work on forgiveness in digital environment*

	Reference	Context	Purpose	Considered factors
Forgiving and forgetting	[102]	Reputation management Information sharing	Facilitating forgiveness in the internet age	---
Forgiving as a factor	[103]	Multi-agent systems	Promoting and reestablishing cooperation	---
	[104]	Noisy environments Multi-agent systems	Promoting and reestablishing cooperation	---
	[105]	Reputation management E-business	Triggering and controlling direct reputation values over time	---
Interpersonal forgiveness	[16]	E-learning	Predicting and encouraging forgiveness	Offence specific Repair strategy Relationship history Empathy
	[9]	Information sharing Multi-agent systems	Using forgiveness as a tool to reevaluate trust after a violation	Forgiveness trait Regret Basic trust Time

2.2.3.2. Forgiveness as a factor

Forgiveness has been introduced as a factor to maintain and encourage cooperation. Riordan [103] proposed a forgiving strategy in a game-theoretic model for multi-agent systems that introduced a forgiveness degree to promote cooperation between agents, by never being the first to defect and by re-establishing cooperation. Although this strategy outperformed other well-known strategies, it is not necessary stable in noisy environments [104]. Moreover, forgiveness is only considered as another strategy for game theory in this case. On the other hand, Burete, Bădică and Bădică [105] has used a forgiveness factor in a reputation model to trigger and control direct reputation values over time in agent societies in e-business. This model reflects an optimistic view of reality, but it ignores the fact that forgiveness is conditional and it cannot always be granted.

Therefore, introducing forgiveness only as a factor may not be the best choice to repair trust in online environments, especially in ongoing relationships. However, it brings a remarkable point of view of the profits a "second chance" can deliver in a purely strategical, unemotional environment.

2.2.3.3. Interpersonal Forgiveness

The third group considers forgiveness to be simply "a prosocial decision to adapt a positive attitude toward another" [15]. To the best of our knowledge, there are only two main research models in this group. The first is a standalone and operational model that predicts forgiveness decision in e-Learning environment with the purpose to facilitate forgiveness and encourage individuals to forgive [15], [16]. This model is built using Takagi-Sugeno fuzzy inference system, with eleven factors: offense severity, offense frequency, intent, apology, action of repair, benefits utility, benefits frequency, visible acknowledgment, prior familiarity, similarity, and propensity to embarrassment. Each factor is associated with a weight distinguishing the degree of influence of each predictor on forgiveness. A recent work by Binmad and Li [106] used a modified version of [16] model in an online Marketplace context. Both model versions can be integrated into different platforms, and be configured for any application. However, their parameters settings are highly dependent on the technical solution and the application domain. Moreover, this model of forgiveness is based on shame and embarrassment, which are not strong factors for predicting forgiveness.

The second model is proposed by Marsh and Briggs [9]. It is a function that computes forgiveness value after an offense between artificial agents in an information-sharing context. This model focused on the act of forgiving more than predicting its value. The constructs that go into their function are: time before forgiving, basic trust between the victim and the offender, the importance of the relationship from the victim view, the regret felt from both sides after the offense, and an individual forgiveness trait for each agent. This forgiveness function is later integrated in a trust function to reevaluate trust values after violation. Compared to the previous model, this one is highly theoretical and it doesn't predict or encourage forgiveness.

2.2.4 Research issues

As one can notice from previous section, interpersonal forgiveness is neglected in the digital environment. This disregard of forgiveness is due to some challenges that make forgiveness research hard to conduct. In this section, we discuss these challenges.

First, users' perception of forgiveness can be misleading, so are their expectations. Forgiveness promote reconciliation but it does not automatically restore a broken relationship or remove the wrong deed/harm. Therefore, when introducing forgiveness, systems' designers should use an appropriate communicative language and a suitable forgiveness definition for their context to familiarize the system users with this concept before exploiting its benefits.

Second, forgiveness may induce vulnerability by encouraging offences and pulling back deserved punishment [8], [16]. As in many systems, users can manipulate them to their advantages. For that, researchers and systems' designers should always keep in mind that forgiveness is conditional.

Third, in order to predict a user's interpersonal forgiveness and facilitate its process, the system may require additional and private information from both the victim and the offender. This can rise privacy issues for both sides. Thus, forgiveness should be optional for system users.

Finally, online social networks have a public appearance. Users tend to filter their online life to please the public and hide their real intents and behaviors. Giving an example, while everyone thought that *Madison Holleran* was a happy, popular and active student based on her Facebook and Instagram accounts, she committed suicide early in her life [107]. Moreover, users' information and actions on the social media (posts, photos, comments, etc.) can be misinterpreted or misleading. In July 20th 2012, *National Rifle Association* sent the following tweet: "*Good morning, shooters. Happy Friday! Weekend plans?*" [108]. Even though the tweet seems very usual, it has been taken out of context by many twitter users because it met the Colorado movie theater shooting [109]. In the same manner, users' forgiveness observations can be misleading. A victim posts may indicate that he/she forgives the offender, while his/her behavior and intentions can be revengeful. Thus, collecting forgiveness data and observing its process is a hard and tricky task that can limit forgiveness research.

2.3 Summary

In this chapter, we introduced the two main concepts that will be encountered throughout the rest of the thesis. We provided an overview of both social trust and interpersonal forgiveness in an online environment in order to familiarize the reader with the context of our work. It is noticeable that interpersonal forgiveness has not been well addressed in a digital environment, more precisely in computer-mediated communications. More attention should be paid to this complex concept in order to benefit from its outcomes in a way to improve online individuals' experiences.

Chapter 3

Facebook[6]

In this chapter, we focus on Facebook as it is the chosen social media platform for our research. We aim in this chapter mainly to investigate Facebook usage purposes by Algerian students, as well as their acceptance and involvement in using it. The study also examines the relationship between Involvement in Facebook and acceptance. The analysis builds upon previous investigations but focuses on students, as they are the participants of this study.

3.1 Motivation

Social networking sites' (SNSs) popularity increased beyond expectations in recent years. Their use can be for a specific context (e.g. **Last.fm**[7] for music, **Goodreads**[8] for books, and **Academia.edu**[9] for academics), or general (e.g. **Facebook**[10] and **Twitter**[11]). According to Alexa traffic rank statistics, the king of social networking sites and the third most frequently visited website on the Internet world wide is Facebook [110]. It also became widely used by students and instructors formally and informally, because it facilitates information sharing, supports

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[6] Parts of this chapter will appear in the following paper:

- Laifa, M. (*In Press*): Facebook Usage, Involvement and Acceptance by Algerian Students. International Journal of Social Media and Interactive Learning Environments.

[7] www.last.fm

[8] www.goodreads.com

[9] www.academia.edu

[10] www.facebook.com

[11] www.twitter.com

communications and encourages social interactions [111], [112]. This gave Facebook a powerful usefulness and importance over other learning platforms.

Although Algeria is the largest country in Africa and the Arab world with an estimated population of 40 million, the adoption of social networks sites was relatively slow. According to a study report conducted by a group of researchers at Dubai School of Government about Arab social media engagement [113], the penetration rates of SNSs in Algeria were 18.1% for Facebook, 2.1% for LinkedIn, and 2.7% for Twitter in May 2014. Despite the fact that Facebook is the most used social network site by Algerians [110], [114], only 6.8 million users were registered in 2014, which represents 8% of Facebook users in Arabic region [113] which is a slow adoption compared to other Arabic countries. The investigation in this chapter contributes to the existing literature in two major ways: first, there is a lack of studies about Facebook use by Algerians in general and Algerian students in particular. Hence, the extent of adoption and perception of Facebook by Algerian students is not known yet. Therefore, we aim to investigate Algerian students' academic and social use of Facebook. Second, our work builds upon existing studies to examine Algerian students' involvement and acceptance of Facebook, which is a primary step to explore the benefits of using Facebook in Academia in developing countries, such as Algeria.

3.2 Facebook use

In the first survey, volunteers were initially asked if they have a Facebook account. Those who answered yes were invited to answer an open question about Facebook use. The question was formed as follows: *"What do you use Facebook for? (Please give at least 3 purposes)".* The question was not precise about academic or social purposes to not limit nor influence participants' answers. Moreover, we asked volunteers about their friends on Facebook by choosing from a list (Family members and friends, students from BBA University, students from other universities, professors /staff from BBA University, professors /staff from other universities).

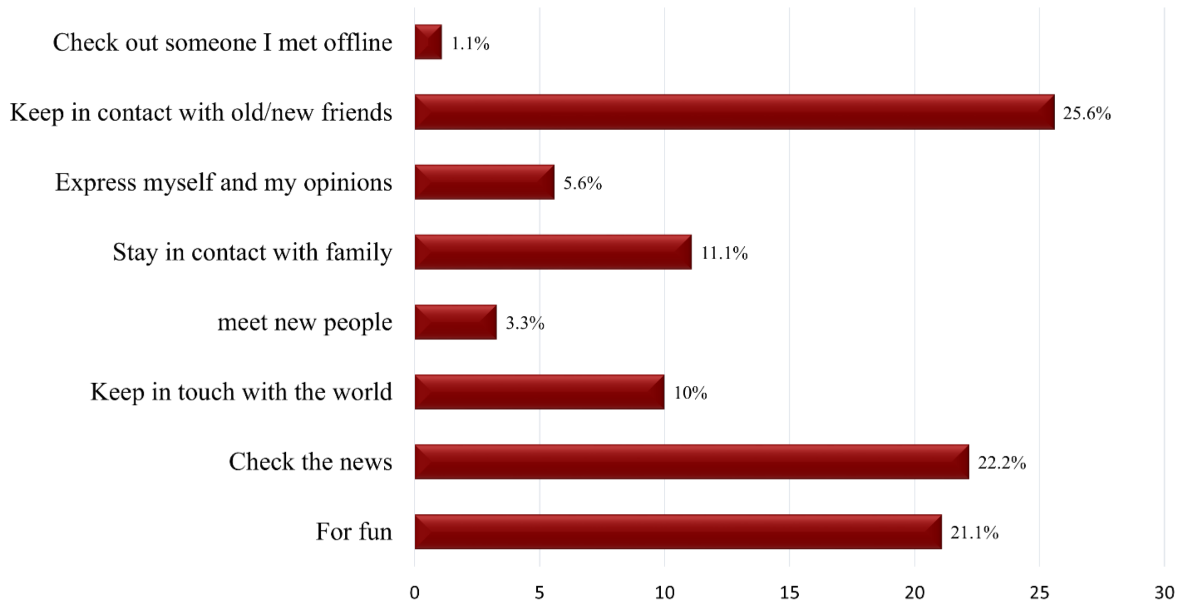


Figure 10. *Social use of Facebook*

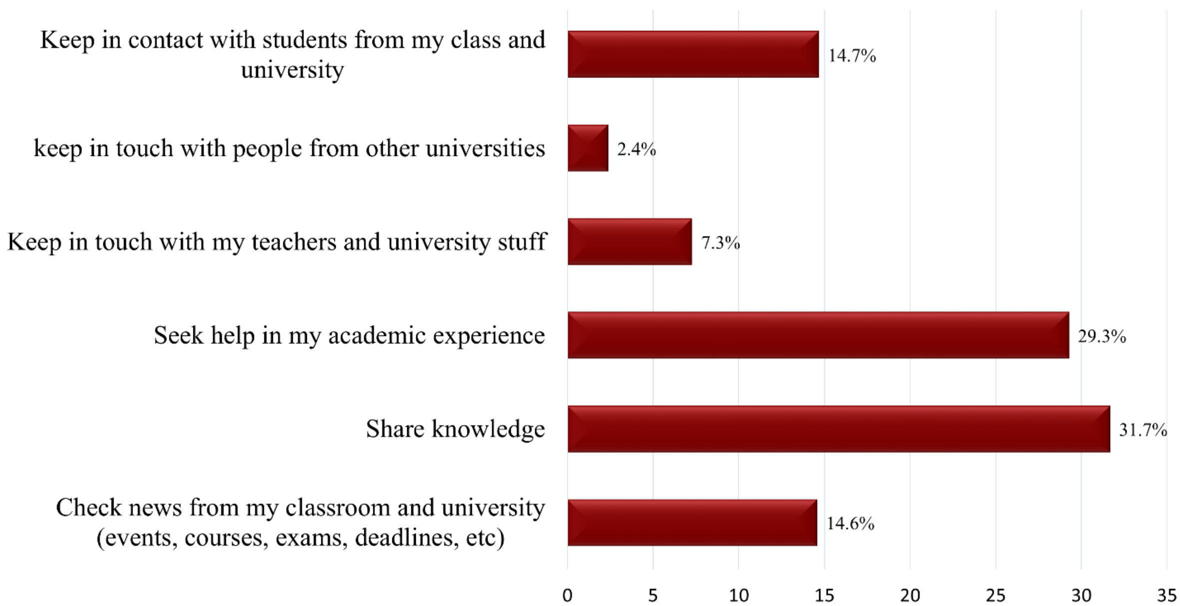


Figure 11. *Academic use of Facebook*

From collected data, 95.3% of students were Facebook members. First, we focus on the open question answers to inquire into whether Facebook is used by students more for social purposes or academic ones. To facilitate the analysis of the responses which were given in their language of choice (Arabic or English), we classified the collected answers into two categories: social purposes and academic purposes. Each category contained a list of purposes (See **Figure 10** and **Figure 11**). For example, given the following quotas:

Respondent-1. " I use it to have fun with my friends. To know everything new. To ask my colleagues at the university for any news about courses and exams."

Respondent-2. "Contacting my family members and friends. For fun. Check the world's news".

We considered the two first purposes in **Respondent-1** to be social, and the third one to be academic, while **Respondent-2** purposes were all social. As shown in **Figure 12**, 69% of reported Facebook usage was for social purposes, while only 31% was for academic aims. Looking deeper into each category, the most common social purposes respondents use Facebook for are: keeping contact with old/new friends (25.6%), checking the news (22.2%) and for fun (e.g. play games) (21.1%). However, their Facebook academic use focuses on sharing knowledge (31.7%) and seeking academic help either from other students or from teachers (29.3%).

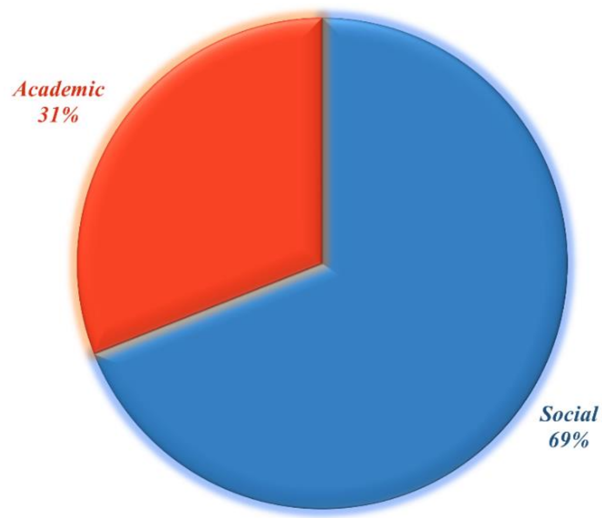


Figure 12. *Facebook usage purposes*

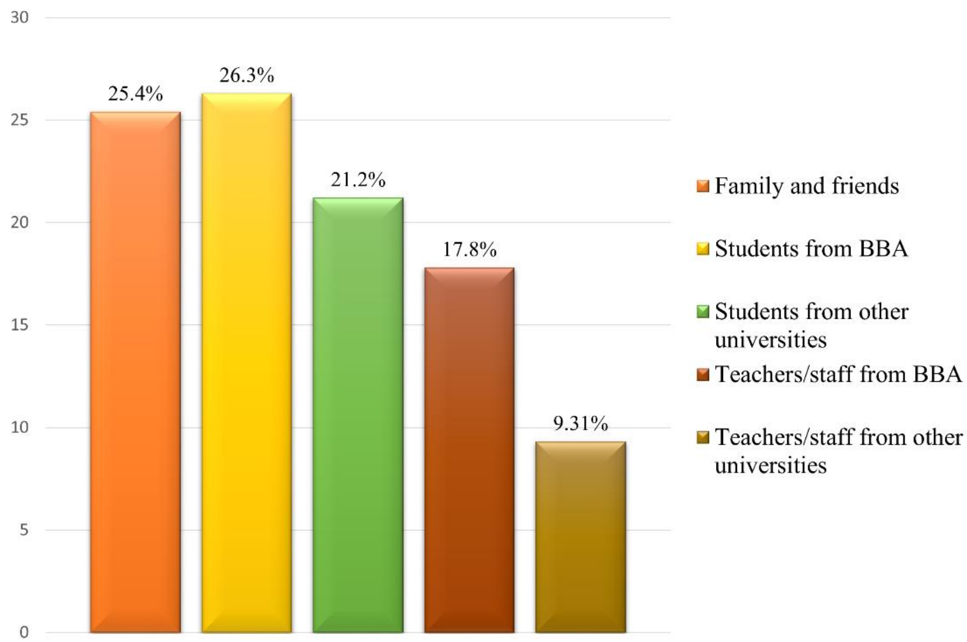


Figure 13. *Participants' Facebook friends*

More insights can be inferred from **Figure 13**. Respondents' Facebook friends seem to be varied with relatively close rates. Adding to family members (25.4%), most students have other BBA University students (26.3%) on their Facebook friends list in addition to students from other Algerian universities (21.2%). They also reported having teachers and staff from our university (17.8%) and from other Algerian universities with the lowest rate 9.31%.

Our data indicated that social purposes dominate Algerian students' use of Facebook. Rather than forming new relationships, Algerian students mainly use Facebook to keep in touch and communicate with their family and friends. In other words, they use Facebook to maintain their existing social relationships, which is similar to Ellison, Steinfield, and Lampe [115] findings. However, owing to the fact that Algerian students also use Facebook as a tool to share knowledge and seek academic help from other students and teachers (either from their university or from other universities), academic relationships are strongly present in their Facebook friends list. This is reflected in the large number of existing Facebook pages and groups of different Algerian universities and faculties. Thus, as emphasized in other studies like [115]–[118], we believe that Facebook is a powerful tool that can enhance Algerian students' academic experience by facilitating communications and encouraging collaborations among students, as well as between students and teachers.

3.3 Respondents' Facebook involvement

Understanding Students' involvement in Facebook use is a substantial step toward investigating Facebook benefits and limitations in a learning context (in addition to further investigations in our research scope). However, to our best knowledge, there is no available literature on Algerians' Facebook involvement in general and Algerian students' in particular. To fill this gap, we focus in this section on collected data about participants' involvement in using Facebook.

Table 2. *Descriptive statistics for Facebook involvement scale items*

Scale items	%	M	S.D
In a NORMAL DAY, how much TOTAL TIME do you spend on Facebook?		3.40	1.42
1 = Less than 20 minutes	13.6		
2 = 20 to 40 minutes	16.1		
3 = 40 minutes to 1 hour	18.6		
4 = 1 to 2 hours	20.1		
5 = More than 2 hours	31.6		
What is the TOTAL number of friends you currently have on Facebook?		1.76	1.13
1 = Less than 100	58.2		
2 = 101 to 200	22.6		
3 = 201 to 300	9.3		
4 = 301 to 400	4.6		
5 = More than 400	5.3		
Emotional connection and integration			
Facebook is important to my university experience		3.44	1.03
Facebook is a part of my everyday activity		3.30	1.14
I am proud to tell people I am on Facebook		2.60	1.04
I feel out of touch when I haven't logged onto Facebook for a while		3.10	1.25
I feel I am a part of the Facebook community		3.25	1.03
I would be sorry if Facebook shuts down		3.13	1.37

To measure Facebook involvement, a scale is needed to not only measure usage frequencies but integration and engagement as well. For this, we adapted [115] scale for measuring the amount of time students spend on Facebook, the number of "*friends*" they have, as well as a series of Likert-scale questions (1 = strongly disagree, 5 = strongly agree) that measure respondents emotional connection to Facebook and to what extent it is integrated in the participants daily routine. The scale internal consistency was α = 0.78.

Table 2 summarizes descriptive statistics for respondents' Facebook involvement. Most respondents reported spending more than an hour (51.7%) on Facebook on a daily basis while more than half of respondents have less than 100 friends on their lists (58.2%). Even though respondents agree or strongly agree that Facebook is important to their university experience (55.5%), and that Facebook is a part of their daily activities (50.1%), they are either neutral (32.5%) or on the disagreed level (48%) when it comes to feeling proud to tell others they are Facebook users, with the lowest mean score (M = 2.6).

For the rest of the items, responses varied. While about 36.4% of respondents don't feel out of touch when they don't log onto Facebook for a period of time and they won't be sorry if it shuts down, about 44.3% reported that they feel otherwise. On the other hand, 45.6% of respondents were on the agreed level for the item "*I feel I am a part of the Facebook community*", when 31.3% were neutral.

Table 3. *Relationship among Facebook involvement variables, age and gender*

***N* = 323**		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Daily time spent on Facebook **(1)**	Pearson correlation Sig. (2-tailed)	1				
Total number of friends **(2)**	Pearson correlation Sig. (2-tailed)	0.247* 0.000	1			
Emotional connection & integration **(3)**	Pearson correlation Sig. (2-tailed)	0.482* 0.000	0.167* 0.003	1		
Gender **(4)**	Pearson correlation Sig. (2-tailed)	-0.049 0.376	-0.525* 0.000	0.046 0.410	1	
Age **(5)**	Pearson correlation Sig. (2-tailed)	0.059 0.291	0.074 0.187	-0.008 0.888	-0.179* 0.001	1

* Correlation is significant at the 0.01 level (two-tailed)

For more insights, we checked the correlations among Facebook involvement variables, respondents' age and their gender as well. The results support the non-existence of multicollinearity as all correlation values are below 0.70. As shown in **Table 3**, there is a significant correlation between the daily time respondents spend on Facebook and their total number of Facebook friends (r = 0.247, p<0.01), and between daily time spent on Facebook and the respondents' emotional connection to Facebook and to what extent it is integrated in their daily routine (r = 0.482, p<0.01). Findings also indicate a correlation between respondents' number of friends and their emotional connection to Facebook (r = 0.167, p<0.01).

The age of respondents does not correlate with any of Facebook involvement variables. However, their gender is strongly correlated with the number of Facebook friends (r = - 0.525, p < 0.01).Male participants (N = 167) were found to have an average of more than 200 Facebook friends (M = 2.34, SD = 1.23). By comparison, female participants (N = 156) had a numerically smaller number of Facebook friends (around 100 or less, with M = 1.15, SD = 0.55). An independent samples *t*-test was performed to test the hypothesis that males and females' numbers of Facebook friends were associated with statistically significantly difference. The independent samples *t*-test was associate with a statistically significant effect, $t(321) = 11.06$, $p < 0.001$. Cohen's *d*[12] was estimated at 1.34, which is a large effect based on [119] guidelines.

3.4 Facebook acceptance

Predicting and explaining users behavior toward new technologies have been widely explored, where many models and theories for new technology acceptance have been proposed [120]–[123]. One of the most powerful models is Davis' Technology Acceptance Model (TAM) [124] (see **Figure 14**) which researchers have used and extended in many studies (e.g. [125]–[129] to cite few). This model is determined by two constructs:

- *perceived usefulness* (i.e. "the degree to which a person believes that using a particular system would enhance his or her job performance") [124]
- *perceived ease of use* (i.e. "the degree to which a person believes that using a particular system would be free of effort") [124].

[12] $d = \frac{M_1 - M_2}{(SD_1 + SD_2)/2}$

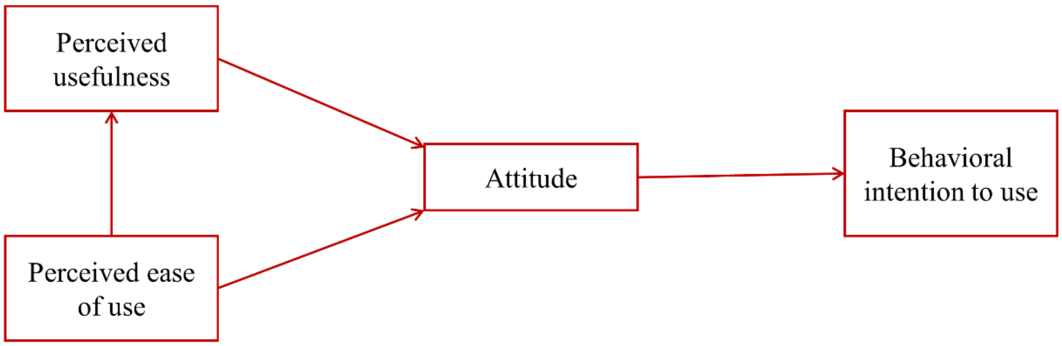


Figure 14. *Davis' Technology Acceptance Model (TAM)[130]*

Another widely used theory for explaining and/or predicting users' intentions and behaviors towards new technologies is the Theory of Planned Behavior (TPB) [131](see **Figure 15**). According to [132]adaptation of the TPB, four important components determine the theory:

- *attitude toward use* (i.e. "one's positive or negative feelings about performing a behavior such as using technology") [132]
- *facilitating conditions* (i.e. "factors in the environment that shape a person's perception of ease or difficulty of performing a task") [132]
- *subjective norm* (i.e. "A person's perception that most people who are important to him or her think he [or she] should or should not perform the behavior in question") [132]
- *behavioral intention* to use (i.e. "The individual's intention to perform a given behavior") [131]

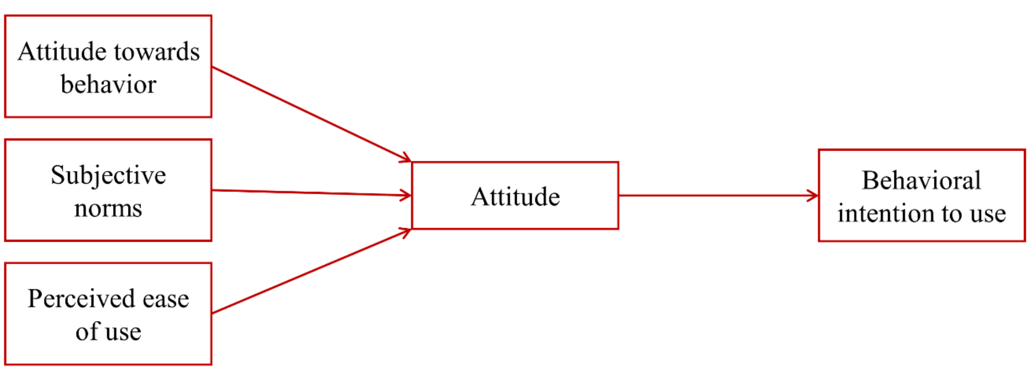


Figure 15. *Theory of Planned Behavior (TPB)[131]*

Perceiving Algerian students' acceptance of Facebook is fundamental for understanding their behavior on Facebook and for farther investigations in next chapter. In this subsection, we inspect two main participants' acceptance of Facebook, then we analyze whether there is a relationship between their Facebook acceptance and their involvement in using Facebook. For this, a questionnaire was adapted from [116] and [132] based on (TAM) and (TPB). The survey contained 13 items (see **Appendix C**) of 5-point Likert-type (1 = strongly disagree, 5 = strongly agree) that measure perceived usefulness (two items with α = 0.74), perceived ease of use (two items with α = 0.70), attitudes toward using (three items with α = 0.72), facilitating conditions (two items with α = 0.71), subjective norms (two items with α = 0.75), and behavioral intention to use (two items with α = 0.67). The internal consistency of the Facebook acceptance scale as whole was α = 0.81. **Table 4** summarizes the mean scores and standard deviations for the scale's variables and items.

Table 4. *Descriptive statistics for Facebook acceptance scale variables and items*

Facebook acceptance Scale	*M*	*S.D*
Perceived usefulness	**2.75**	**0.94**
Using Facebook enhances my effectiveness	2.90	1.04
Using Facebook increases my productivity	2.60	1.07
Perceived ease of use	**3.90**	**0.75**
My interaction with Facebook is clear and understandable	3.61	1.00
I find Facebook easy to use	4.20	0.82
Attitude toward use	**3.28**	**0.83**
Facebook makes life more interesting	2.76	1.13
Working with Facebook is fun	3.44	1.01
I like using Facebook	3.64	0.96
Facilitating conditions	**3.16**	**0.87**
When I need help to use Facebook, guidance is available to me	3.28	1.02
When I need to use Facebook, a specific person is available to provide assistance	3.05	1.12
Subjective norm	**2.90**	**0.98**
People whose opinions I value encourage me to use Facebook	2.85	1.06
People who are important to me support me to use Facebook	2.93	1.12
Behavioral intention to use	**3.20**	**0.92**
I will use Facebook in the Future	3.45	1.01
I plan to use Facebook often	2.96	1.14

The lowest overall mean score was reported for Facebook *perceived usefulness* (M = 2.75). The findings show that 31.6% of respondents agreed that Facebook enhances their effectiveness whereas 30.9% disagreed and 37.5% were neutral. However, half of respondents (50.8%) disagreed or strongly disagreed that Facebook increases their productivity, while only 24.2% were on the agreed level. On the other hand, *perceived ease of use* variable was the highest overall mean score of Facebook acceptance (M = 3.90), where most of respondents agreed or strongly agreed that their interaction with Facebook is clear and that Facebook is easy to use (65%, 88.3% respectively).

The second highest overall mean score of Facebook acceptance variables was for *attitude toward use* (M = 3.28), where 52% of respondents agreed that working with Facebook is fun, and 62.9% liked using Facebook. Nevertheless, 40.9% were on the disagreed level with the first item (i.e. Facebook makes life interesting), and 31.9% were neutral. However, the overall means of participants were neutral for *Facilitating conditions, subjective norm* and *behavioral intention to use* (M = 3.16, M = 2.90, M = 3.20 respectively).

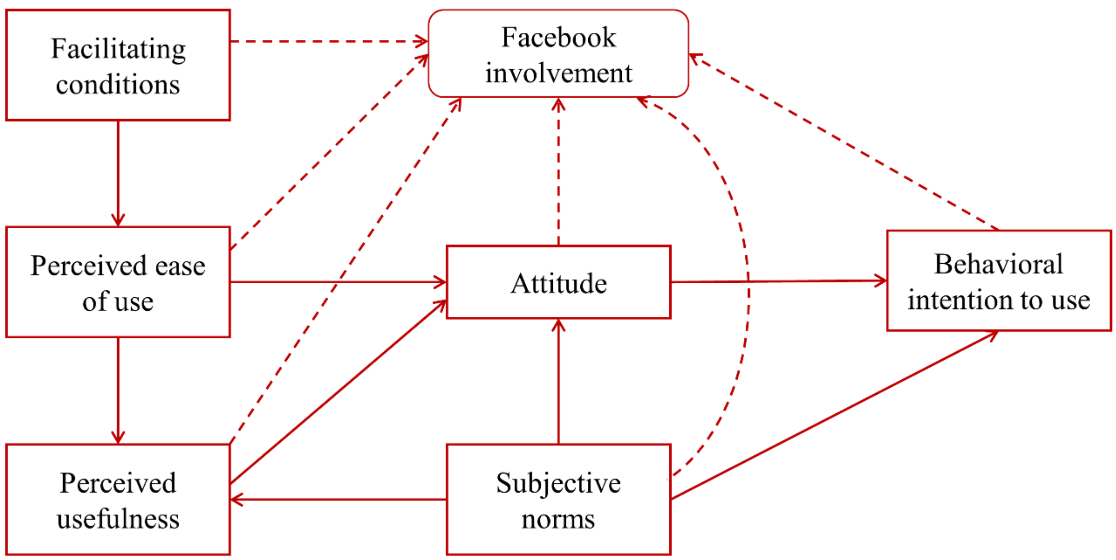


Figure 16. *Extended model of Teo [132]*

3.5 Relationship between Facebook acceptance and involvement

To investigate to which Facebook acceptance can influence users' Facebook involvement, an extension of [132] model was developed. In the original model, Teo [132] combined the TAM and TPB explained in the previous section. The model is illustrated in **Figure 16** with rectangles that represent model's variables, and full arrows between them according to their effects.

In the extension version, we examine if Facebook acceptance constructs influences Facebook involvement (that are: perceived ease of use, perceived usefulness, subjective norms, facilitating conditions, attitude to use, and behavioral intentions). These paths are added to Teo [132] model as dashed arrows in **Figure 16** above. Multiple regression analysis will be used to assess the significance of the added effects.

3.5.1 Correlation analysis

Table 5 shows the correlations among respondents' age, gender, Facebook involvement and acceptance. The age and gender of respondents didn't correlate with neither Facebook acceptance nor involvement. The only strong correlation the findings indicate is between respondents' Facebook acceptance and their involvement (r = 0.606, p<0.01). For a further perception of the results, correlations among Facebook acceptance variables and involvement variables are shown in **Table 6**. As the findings indicate, the *total number of Facebook friends* variable doesn't correlate with any of Facebook acceptance variables. Otherwise, the *daily time spent on Facebook* weakly correlate with *perceived ease of use* (r = 0.283, p<0.01), *attitude toward use* (r = 0.272, p<0.01), and *behavioral intention to use* (r = 0.208, p<0.01).

Table 5. *Correlations among Facebook involvement, acceptance, gender and age*

***N* = 323**		**(1)**	**(2)**	**(3)**	**(4)**
Facebook Involvement **(1)**	Pearson correlation Sig. (2-tailed)	1			
Facebook Acceptance **(2)**	Pearson correlation Sig. (2-tailed)	0.606* 0.000	1		
Gender **(3)**	Pearson correlation Sig. (2-tailed)	-0.075 0.179	0.022 0.689	1	
Age **(4)**	Pearson correlation Sig. (2-tailed)	0.022 0.689	0.093 0.096	0.179* 0.001	1

* Correlation is significant at the 0.01 level (two-tailed)

However, the results suggest that *emotional connection and integration* of Facebook in respondents' life correlates with all Facebook acceptance variables. **Table 6** shows a strong significant correlation between *emotional connection and integration* of Facebook and *attitude towards use* (r = 0.603, p<0.01), and *behavioral intention to use* (r = 0.516, p<0.01). It also indicates that emotional connection and integration of Facebook moderately correlate with *perceived usefulness* (r = 0.397, p<0.01), *perceived ease of use* (r = 0.416, p<0.01), and subjective norm (r = 0.324, p<.01). Finally, the findings show a significant but weak correlation between *emotional connection and integration* of Facebook and *facilitating conditions* (r = 0.245, p<0.01). The results support the non-existence of multi-collinearity as all correlation values are below 0.7.

Table 6. *Correlations between Facebook acceptance variables and Facebook involvement variables*

***N* = 323**		Daily time spent on Facebook	Total number of friends	Emotional connection & integration
Perceived usefulness	Pearson correlation Sig. (2-tailed)	0.099 0.076	0.055 0.324	0.397* 0.000
Perceived ease of use	Pearson correlation Sig. (2-tailed)	0.283* 0.000	0.102 0.067	0.416* 0.000
Attitude toward use	Pearson correlation Sig. (2-tailed)	0.272* 0.000	0.050 0.373	0.603* 0.000
Facilitating conditions	Pearson correlation Sig. (2-tailed)	0.650 0.246	0.027 0.627	0.245* 0.000
Subjective norm	Pearson correlation Sig. (2-tailed)	0.075 0.178	0.054 0.335	0.324* 0.000
Behavioral intention to use	Pearson correlation Sig. (2-tailed)	0.208* 0.000	0.099 0.075	0.516* 0.000

* Correlation is significant at the 0.01 level (two-tailed)

3.5.2 Regression analysis

Following many similar studies such as [115], [133]–[137], multiple regression analysis was chosen to test the relationship between the set of predictors and the dependent variable in the model. Many assumptions were tested to assure that the used data is applicable for multiple regression analysis. **Figure 17** represent a general regression equation.

Dependent variable *Predictors*

$$\hat{Y} = \underbrace{b_0}_{\text{Estimated intercept}} + b_1 X_1 + b_2 X_2 + \cdots + b_i X_i$$

Estimated coefficients

Figure 17. *Regression equation presentation*

An analysis of standard residuals was carried out on the data to identify any outliers, which showed that the data contained no outliers (*SD. Residual Min* = -3.08, *SD. Residual Max* = 2.37). In addition, Tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern as *VIF* values are less than 10 and *Tolerance* values are greater than 0.1 (see **Table 7**).

To test the independence of observations, Durbin-Watson test was used. The data met the assumption of independent residuals (Durbin-Watson value = 1.92). On the other hand, the histogram of standardized residuals in **Figure 18** indicated that the data normally distributed, as did the normal P-P plot in **Figure 19**, which showed points that were very close to the line. Finally, the data met the assumptions of homoscedasticity and linearity as shown in the scatterplot of standardized residuals in **Figure 20**.

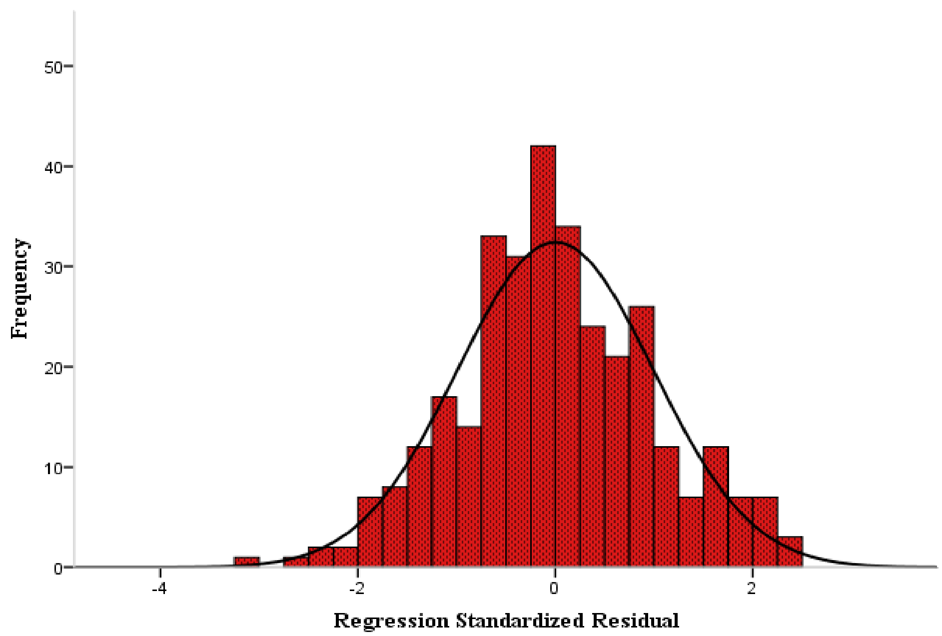


Figure 18. *The histogram of standardized residuals*

$$\boldsymbol{Facebook\ Involvement} = \boldsymbol{b_0} + \boldsymbol{b_1}\text{Facilitating Conditions} + \boldsymbol{b_2}\text{Perceived ease of use} + \boldsymbol{b_3}\text{Perceived Usefulness} + \boldsymbol{b_4}\text{Attitude} + \boldsymbol{b_5}\text{Subjective Norms} + \boldsymbol{b_6}\text{Behavioral Intention}$$

The equation used for Facebook involvement prediction is expressed above. Using the enter method; it was found that *subjective norms* and *facilitating conditions* did not significantly predict participants' Facebook involvement. However, *behavioral intention* to use, *attitude to use*, *perceived ease of use* and *perceived usefulness* did significantly predict Facebook involvement (see **Table 7**).The original Teo [132] model was also verified using regression method. **Table 8** summarizes the regression weights of different paths between variables. All estimates were found significant which is in line with [132] findings.

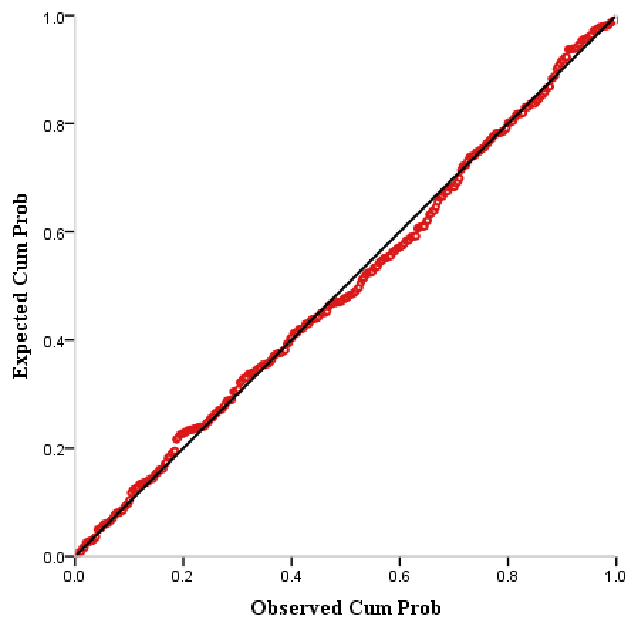


Figure 19. *The normal P-P plot of standardized residuals*

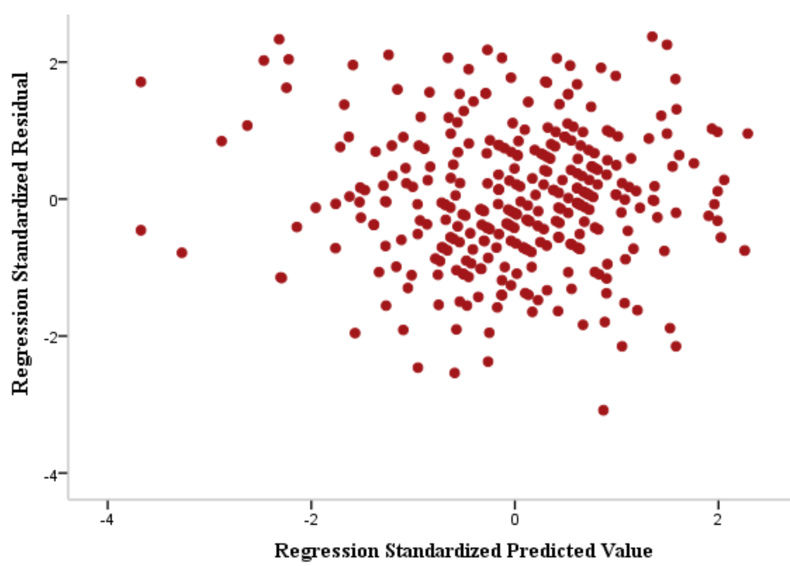


Figure 20. *The scatterplot of standardized residuals*

Table 7. Predicting Facebook involvement

Predictors (R^2 = 0.407)	**β**	***t***	***p******	**Collinearity statistics**	
				Tolerance	**VIF**
Behavioral intention to use	0.20	3.78	0.000	0.665	1.503
Perceived usefulness	0.10	2.01	0.040	0.793	1.262
Perceived ease of use	0.20	3.83	0.000	0.800	1.250
Attitude to use	0.32	5.76	0.000	0.598	1.672
Subjective norms	0.007	0.13	0.880	0.790	1.265
Facilitating conditions	0.06	1.46	0.140	0.917	1.09

* $p < 0.05$

Table 8. Regression weights for original Teo model

Outcome	**Predictors**	***β***	***t***	***p******
Behavioral intention to use (R^2 = 0.307)	Attitude to use	0.46	9.30	0.000
	Subjective norms	0.17	3.31	0.001
Perceived ease of use (R^2 = 0.170)	Facilitating conditions	0.18	3.098	0.002
Perceived usefulness (R^2 = 0.113)	Perceived ease of use	0.17	3.110	0.002
	Subjective norms	0.25	4.641	0.000
Attitude to use (R^2 = 0.311)	Perceived ease of use	0.30	5.946	0.000
	Perceived usefulness	0.26	5.349	0.000
	Subjective norms	0.23	4.658	0.000

* $p < 0.05$

3.6 Discussion

Even though the Algerian students' average number of Facebook friends was low (less than 100), the average daily time they spend on Facebook (more than an hour) was higher compared to other studies conducted in developed countries [115], [116], [138]. Further, the analysis indicated a strong correlation between the daily time spent on Facebook and its integration in participants' social life. The findings also showed a moderate emotional connection and integration of Facebook in Algerian students' routines, and that they considered it to be important for their academic experience. This explains the large amount of time they spend on Facebook in a daily basis, and the fact that they have many academic connections on their Facebook. However, most students do not feel proud to tell people they are on Facebook. It might be due to the Algerian politics, and complexity and diversity of the Algerian society, which still limit freedom of expression and technology adaptation [139]–[141]. In addition, and contrary to McAndrew and Jeong [142] study, Algerian male students tend to have more Facebook friends than their female peers. Due to the limited scope of this study, further investigation is required to perceive the reasons behind this difference.

According to [133]'s TAM, perceived usefulness is more influential in technology or system usage behavior than perceived ease of use. The findings in our study indicated that Algerian students do not strongly believe that a positive relationship exists between positively using Facebook and their performances (low perceived usefulness), but they show high to moderate levels of perceived ease of use, attitude toward use, facilitating conditions, subjective norms, and behavioral intention to use Facebook. Conceptually, this may explain the slow adoption of Facebook by Algerians, where many users reported that social networks in general waste their time and that they rise many privacy issues in such a conservative society [114]. However, further social and psychological research is needed for better understanding of this matter.

Algerian students' attitude towards using Facebook strongly affected their behavioral intention to use Facebook and their Facebook involvement, which is supported by the original Ajzen [137] model that asserts that user's attitude toward using a technology or a system can portend intentions to fulfill or perform his/her behavior. Furthermore, participants' Facebook acceptance was found to predict their Facebook involvement, In accordance with other studies, this relationship suggests that the more users accept Facebook the more involved they get into it [116], [132].

3.7 Summary

The purpose of this chapter was to investigate Algerian students' use of Facebook, their Facebook involvement and acceptance, which is an elementary step to our research. Eventually, the current work was the first to examine Algerian students' perception and involvement of Facebook. Due to the lack of studies about this matter, the study calls for further investigations from different disciplines to provide a larger understanding and encompassing perspective on Facebook use and benefits in developing countries.

Chapter 4
Theoretical Model[13]

Interpersonal relationships' structures and standards are evolving. By focusing on a social network context, this chapter examines different factors that can affect forgiveness decision of a victim of an online offense. In addition, it inspected trust dynamics and whether the decrease of trust after an online-related offense can be affected by forgiveness.

4.1 Theoretical framework and Hypotheses

As explained in **Section 2.2**, forgiveness has many definitions in literature. As we focus in our settings on ongoing relationships, we adopt Rusbult et al. [12] definition for interpersonal forgiveness, that is: "*the victim's willingness to resume pre-transgression interaction tendencies—the willingness to forego grudge and vengeance, instead coming to behave toward the perpetrator in a positive and constructive manner*". We will focus in our research model only on the most influential factors, which are: empathy, commitment and offense specific factors [10], [92]. **Figure 21** below depicts the theoretical research model of this study. Next, we explain different hypotheses behind this model. The common Structural Equation Modeling format of representation of the variables was used, where unobserved variables (latent) are presented in

[13] Parts of this chapter will appear in the following paper:

- Laifa, M., Imani G.R. Akrouf, S., & Maamri, R. (2018): Forgiveness Predictors and Trust in a Digital Environment. International Journal of Technology and Human Interaction (IJTHI), 14(4) circles or ellipses, and observed (measured) variables are presented in rectangles. The single headed arrows (paths) are used to highlight the casual relationships between variables.

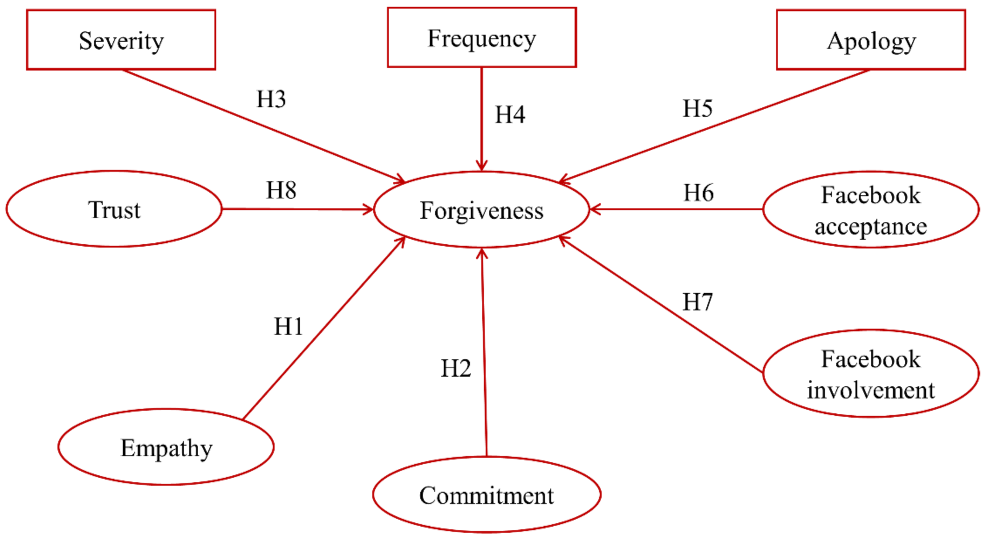


Figure 21. *Research Model*

Empathy

Humans' social and cognitive nature drives victims to walk in their offenders' shoes, especially if the victim has committed the same transgression in the past. This fact propelled scholars to study empathy consequences on interpersonal forgiveness decision [16], [93], [100]. Empathy means perceiving an event from the offender's perception, cognitively and emotionally [143]. According to McCullough et al. [92], [96] experiments, victims' level of empathy highly and positively correlates with their forgiveness. Riek and Mania [10] confirmed these findings in their meta-analysis of 103 papers on forgiveness and a number of predictors and outcomes. One possible explanation for empathy's influence is that it facilitates the motivational changes and mediates the relationship between forgiveness and other factors. Following these studies in offline settings, we hypothesize that in a social network context:

H1: Empathy affects forgiveness positively.

Commitment

When it comes to relationship characteristics' influence on interpersonal forgiveness, scholars agree that commitment is one of the most influential factors on the reaction of victims to an offense [98]. Commitment is necessary to continue a relationship after the happening of a wrong deed. It is defined as "*the extent to which each partner intends to persist in the relationship, feels psychologically attached to it, and exhibits long-term orientation toward it*" [12]. Thus, scholars who studied interpersonal forgiveness also consider commitment's impact on it [8], [10], [92], [96], [144]. For example, Finkel and his colleagues [98] conducted three studies on commitment-forgiveness association in close relationships using a survey and an interaction record study, which supported the assumption that commitment increases pro-relationship motivations and interpersonal forgiveness. Accordingly, we hypothesize that in a social network context:

H2: Commitment affects forgiveness positively.

Offense-specific factors

In the offline world, severe and frequent offenses are more difficult to forgive as confirmed by many experiments in psychology. For example, Riek and Mania's meta-analysis [10] proved that the severity of the offense negatively affects interpersonal forgiveness. In addition, Fincham et al. [97] examined subjective and objective offense's severity and revealed that both perspectives predicted forgiveness and affected it negatively. Moreover, Gunderson and Ferrari [145] indicated that victims of infidelity in romantic relationships are more likely to forgive a cheating that happened only once regardless of how it was discovered. Hence, we assume that in a social network context:

H3: The severity of the offense affects forgiveness negatively.

H4: The frequency of the offense affects forgiveness negatively.

On the other hand, the link between apology and forgiveness was found to be strong in many studies within different offline settings. Although apology is not necessary for the victim to forgive the offender, participants in some studies were more likely to forgive even severe offenses, in the presence than absence of an apology [92], [145]. Consequently, we posit that in a social network context:

H5: Apology affects forgiveness positively.

Acceptance of and involvement in Facebook

Human behavior is massively shifting due to the collective cultural acceptance of social media and the heavy involvement of users in it. According to Hampton and his colleagues [2], Internet and social media users report more close and diverse relationships than non-users, where, for instance, Facebook users reported 10% more close ties than average internet users. Moreover, it was found that people who use technology while engaging/interacting had more positive perceptions about their relationships [3]. Consequently, the impact of the used technology should be considered when analyzing forgiveness. In our model, we examine two factors: users' acceptance of and involvement in the social network platform on which the offense takes place, and we hypothesize that:

H6: Victim's acceptance of the social platform has a positive impact on forgiveness decision.
H7: Victim's involvement in the social network platform positively affects forgiveness.

Forgiveness and Trust dynamics

Another factor that can affect forgiveness decision is the victim's pre-transgression trust in the offender. Interpersonal trust can be defined as the strength of the trustor's belief that the trustee will act as expected and in the best interest of the trustor, within a determined context and at a given time [146], [147]. It is claimed that trust encourages motivation and willingness to engage in prosocial behaviors (e.g., accommodation and sacrifice) [12]. Such prosocial behaviors increase the likelihood of victims to forgive an intentional offense. Therefore, the last hypothesis in our model is as follows:

H8: Pre-transgression Trust positively affects forgiveness.

On the other hand, trust is dynamic and very sensitive. It may evolve with positive experiences, and decay after negative ones. Although trust dynamic has attracted many researchers, there is still a lack of effort on studying and modeling forgiveness as a tool to control trust dynamics.

In psychology, Fincham [144] and Rusbult et al. [12] argued that forgiveness is one important way to maintain healthy relationships. Moreover, Marsh and Briggs [9] discussed the important role forgiveness can play in revaluating trust between agents in a digital environment. Their trust revaluation after a transgression takes into account forgiveness and the trust value before the transgression. In addition, Vasalou, Hopfensitz, and Pitt [148] compared three reputation systems: one that supports apology and one that supports both apology and forgiveness, to a simple reputation system. Their experiments revealed that, in contrast to the other systems, the reputation system with forgiveness component restores the victim's trust directly after the transgression.

However, victim forgiveness of an offense does not ensure reconciliation (i.e., "*the resumption of pre-transgression relationship status*" [12]). Further, Karremans and Van Lange [11] experiments revealed that not forgiving an offender decreased the victim's positive motivations, while forgiving restored rather than increased the levels of pro-relationship motivations. Accordingly, trust level will decrease after an offense. For an encompassing perspective of trust dynamic when a victim tends to forgive their offender, we aim to answer the following question in our study:

Q1: In the presence of forgiveness, does trust level decrease significantly after an offense?

4.2 Methods

4.2.1 Procedure and measurements

In the first survey (**Appendix B**), participants were invited to mention *at least three* activities they undertake on Facebook with friends they *trust* and three acts on Facebook they consider to be offensive and hurtful (whether the acts happened to them personally or not).

In the second survey (**Appendix C**), participants anonymously completed several measures, all using 5-point scales (1= strongly disagree, 5 = strongly agree). After the informed consent, they were invited to describe their feelings about different statements concerning their Facebook acceptance and involvement, as well as empathy items. Then, they were asked to bring to mind a Facebook friend they trust, and rate different trust and commitment items (explained next) relating to the friend they have in mind. Next, participants read a randomly assigned scenario in which they were asked to imagine that the friend they had in mind committed a hypothetical transgression. Each scenario contained: (a) *a hypothetical offense* (hacking the participant's Facebook account vs sharing a photo of the participant without permission), (b) *apology for the act* (apology vs no apology) and (c) *the frequency of the offense's occurrence* (only once vs many times). All used scenarios can be found in **Appendix D**.

After that, participants rated the severity of the offense (subjectively), then they completed forgiveness and trust scales after the hypothetical offense happened. The survey ended with demographic questions.

Trust

Measuring trust depends on the context and the purpose of the study [149]. Many trust scales have been developed and used in the literature. As explained in previous sections, we focus on social interpersonal trust with two main aspects: *belief and behavior*. Inspired by McKnight et al. [146] framework and Nepal et al. [55] trust model, we used two sub-scales; one for measuring trust belief, and one for trusting behavior.

Trust belief was measured using a modified version of McKnight [146] scale, which assessed benevolence (3 items, $\alpha = 0.81$) and integrity (2 items, $\alpha = 0.92$).

Based on participants answers from the first survey about different activities they perform on Facebook with friends they trust, a trust behavior measure was developed using also a 5-point Likert scale ($\alpha = 0.77$). Participants rated four statements pertaining to trust behavior towards the friend they were asked to bring to mind (See **Appendix C**). The internal consistency of pre-transgression trust measure as a whole was $\alpha = 0.88$.

To measure trust after the hypothetical offense, the wording of the same trust measures was slightly refined (using future tense instead of present tense when necessary). The internal consistency of trust after the offense scale as a whole was $\alpha = 0.93$, with the subscales Cronbach alpha as follows: benevolence ($\alpha = 0.87$), integrity ($\alpha = 0.93$), and trust behavior ($\alpha = 0.89$).

Forgiveness

Forgiveness was assessed using the **TRIM** (i.e., transgression-related interpersonal motivations) inventory developed by McCullough and his colleagues [92]. The TRIM inventory measures two distinct motivations (i.e., avoidance and revenge). Ten items of this originally twelve-item measure were used, with seven items measuring the avoidance component ($\alpha = 0.95$) and three items measuring the revenge component of forgiving ($\alpha = 0.83$). The two discarded items were deleted because they caused redundancy after being translated to Arabic. The measure had a very good internal consistency ($\alpha = 0.93$).

Offense-specific factors

The severity of the offense was assessed using a 3-point Likert scale item (i.e., How severe is this offense to you?) with 1 = Not severe at all, 2 = Somewhat severe, 3 = Extremely severe. However, the occurrence frequency of the hypothetical offense and the apology of the offender were embodied in the scenario, which later were coded using a binary scale for the analysis.

Facebook acceptance and involvement

Respondents' Facebook acceptance was measured by 5-point Likert type items that were adopted from the technology acceptance model and the theory of planned behavior. The used scales for measuring participants' acceptance of and involvement in using Facebook are explained in **Sections 3.3 and 3.4**.

Empathy

Participants' empathy was assessed using a modified version of Loewen [143] empathy quotient (EQ). The original measure contained eight items, then three items were deleted after the pretest phase where most volunteers for the test claimed that those items were confusing and unclear (because they couldn't be translated in a way that their connotations corresponded in English and Arabic). Two items with reversed scores were also excluded due to non-significant factor loadings and to boost internal consistency. The resulting scale contained three items and had an internal consistency of $\alpha = 0.71$.

Commitment

Participants indicated, on a four-item scale, their commitment to the friend they brought to mind. The scale items included feelings of attachment (e.g. 'I feel very attached to our relationship – very strongly linked to him/her') and intents to persist and maintain the relationship for a long term (e.g. 'I want our relationship to last forever') [11], [150]. This measure had a very high internal consistency ($\alpha = 0.93$).

4.2.2 Structural equation modeling

Causal relationships between the theoretical framework model's constructs were examined using Structural Equation Modeling (SEM) method with AMOS software. SEM consists of a varied set of mathematical models, computer algorithms, and statistical methods that fit grids of constructs to specific data. There are some other alternative methods such as Partial Least Squares

(PLS) Latent Class Analysis (LCA) models. However, PLS is objectionable as it relies too much on simple assertions that are not always supported by rigorous analysis. Moreover, PLS method is designed to maximize prediction rather than fit by maximizing the proportion of variance of the dependent "construct" that is explained by the predictor "constructs", whereas SEM is designed to maximize and then test the degree of consistency between models and data to find best fit. On the other hand, LCA models is suitable when both the measure and the underlying latent variable are essentially categorical, which is not the case of our model's constructs.

Use of SEM is commonly justified in different fields because of many advantages. For instance, SEM can provide separate estimates of relations among latent constructs and their indicators (i.e., the measurement model) and of the relations among constructs (i.e., the structural model) [23], [151], [152]. In addition, SEM allows testing models with multiple levels of hierarchically structured data [23]. Another known advantage of SEM is the ability to model mediating variables and model error terms [23], [151].

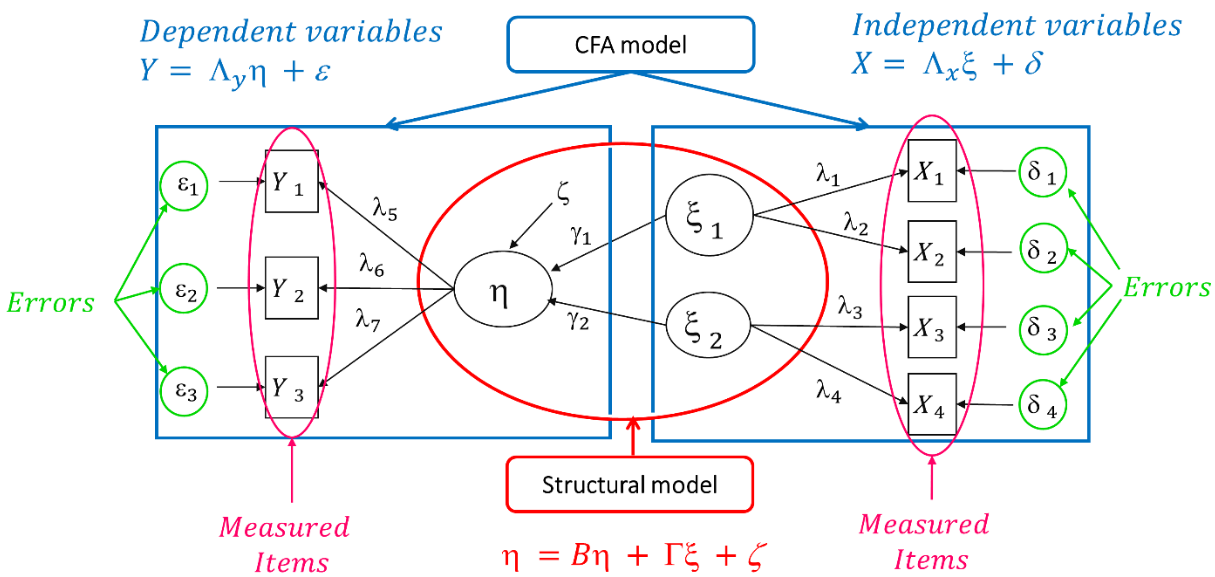


Figure 22. *A simple example of a structural equation model with two CFA models*

In this work, a two-stage procedure was applied to the measurement model (aka. CFA for Confirmatory Factor Analysis) and the structural model. **Figure 22** illustrates a simple example of a structural equation model with two CFA models and one structural model, where three equations and terms in the SEM are defined as follows. First, the structural model equation is:

$$\eta = B\eta + \Gamma\xi + \zeta$$

B is an $m \times m$ matrix of structure coefficients of the η-variables in the structural relationship; Γ is an $m \times n$ matrix of coefficients that relate ξ to ; η $(m \times 1)$ and ξ $(n \times 1)$ are random vectors of latent variables; and ζ is an $m \times 1$ vector of equation errors in the structural relationship between η and ξ. The measurement model for X and Y is constructed as follows:

$$Y = \Lambda_y \eta + \varepsilon$$
$$X = \Lambda_x \xi + \delta$$

Y is a $p \times 1$ vector of outcome (dependent/endogenous) variables; X is a $q \times 1$ vector of input (independent/exogenous) variables; Λ_y *$(q \times m)$ and* Λ_x *$(q \times n)$ are the* matrices of factor loadings of Y and X on η *and* ξ respectively; δ is a $q \times 1$ vector of measurement errors in X; and ε $(p \times 1)$ is a vector of measurement errors in Y. **Figure 23** represent the forgiveness model using AMOS.

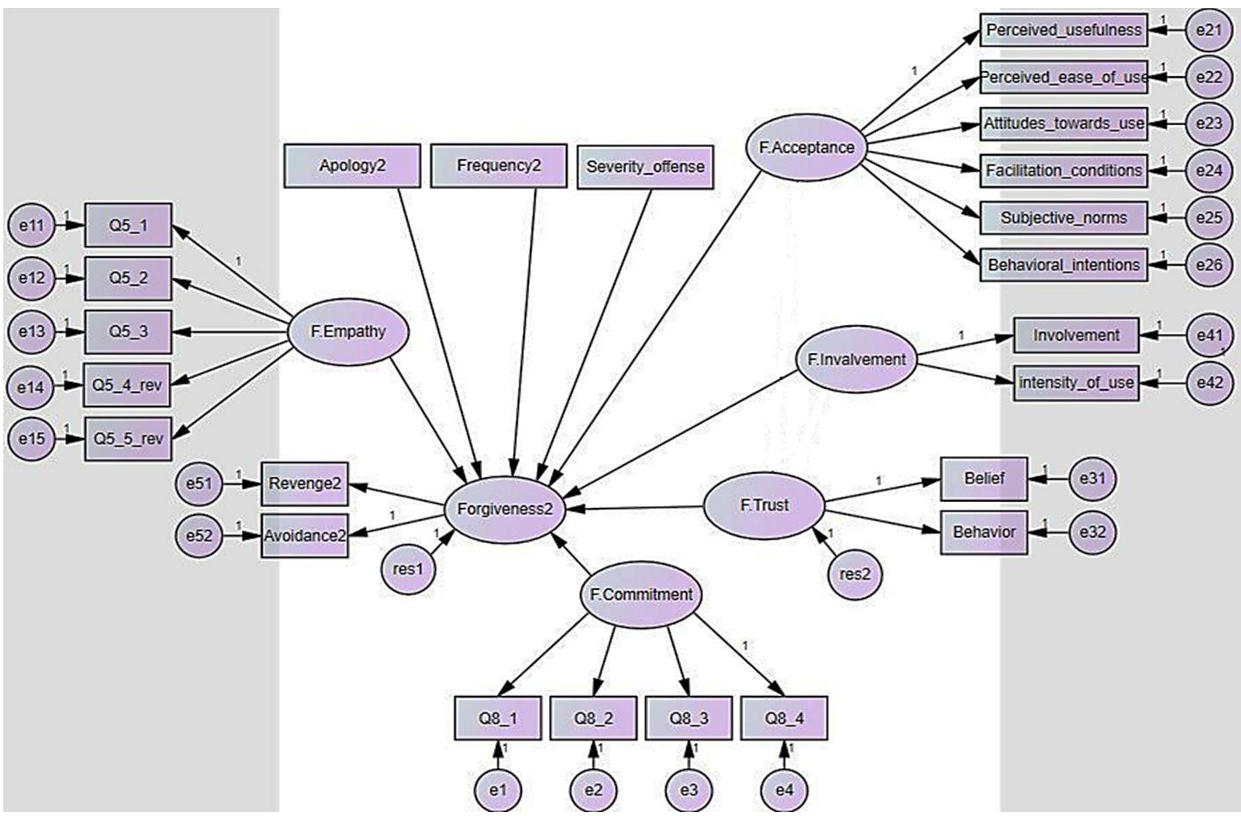


Figure 23*. Forgiveness SEM model using AMOS*

4.3 Results

This analysis section includes an examination of data from both surveys' responses and the descriptive statistics of the measurements. The reliability and validity of the used measurements are also assessed in this section, followed by an evaluation of the proposed research model and a test of the hypotheses.

4.3.1 Trust behavior and offensive acts

The purpose of the first survey was to investigate the behaviors that Facebook users usually perform with their trusted friends on Facebook, along with those acts they consider to be offensive or harmful.

To simplify the analysis and findings report, all responses were classified into lists. **Figure 24** shows a list of different behaviors participants perform with their trusted friends on Facebook. The list contains 06 main behaviors (vis. Sharing posts with them, commenting on their posts, liking their posts, chatting, checking their new posts, and playing Facebook games with them). Few responses that didn't fit in any of the proposed options were considered as "others". The most common behaviors respondents reported were private messaging with their trusted friends (23%), interacting to their posts either by liking (13.7%) or leaving comments (14.1%) and sharing posts with them on their Facebook walls or by tagging them (21.5%). In addition, many respondents reported that they frequently check their trusted friends' new posts on their Facebook walls (18.9%). Those common answers were used to create a trust behavior measurement in the second survey.

In the same manner, responses about offensive behaviors have been assorted in a list as shown in **Figure 25**. The most common offensive acts on Facebook as reported by respondents are: being hacked by a friend on Facebook (34.6%) and sharing their photos without their permission (18.9%). Therefore, these two transgressions were chosen as the hypothetical offenses in the second survey.

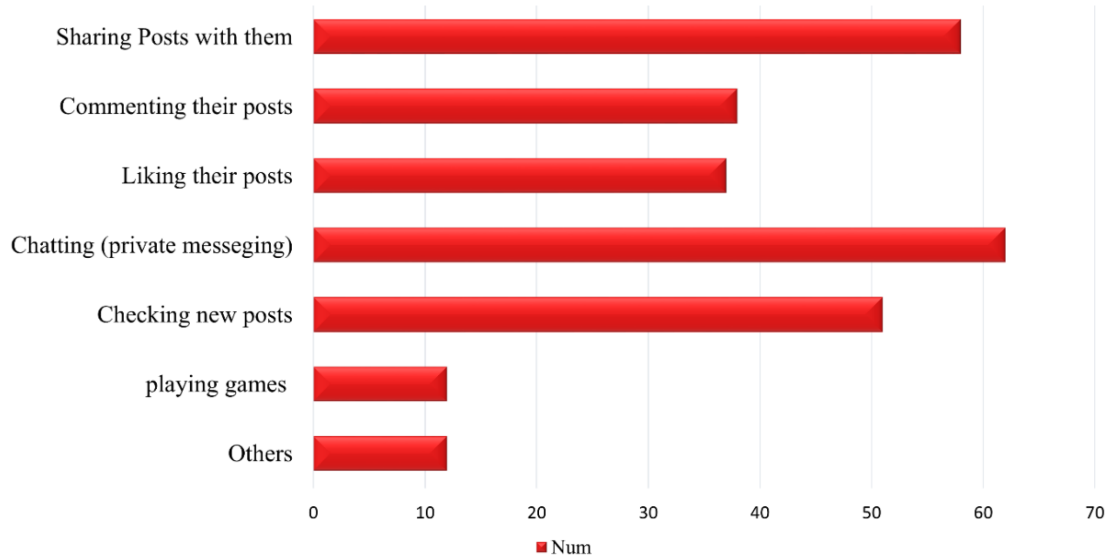


Figure 24. *Trusting behaviors*

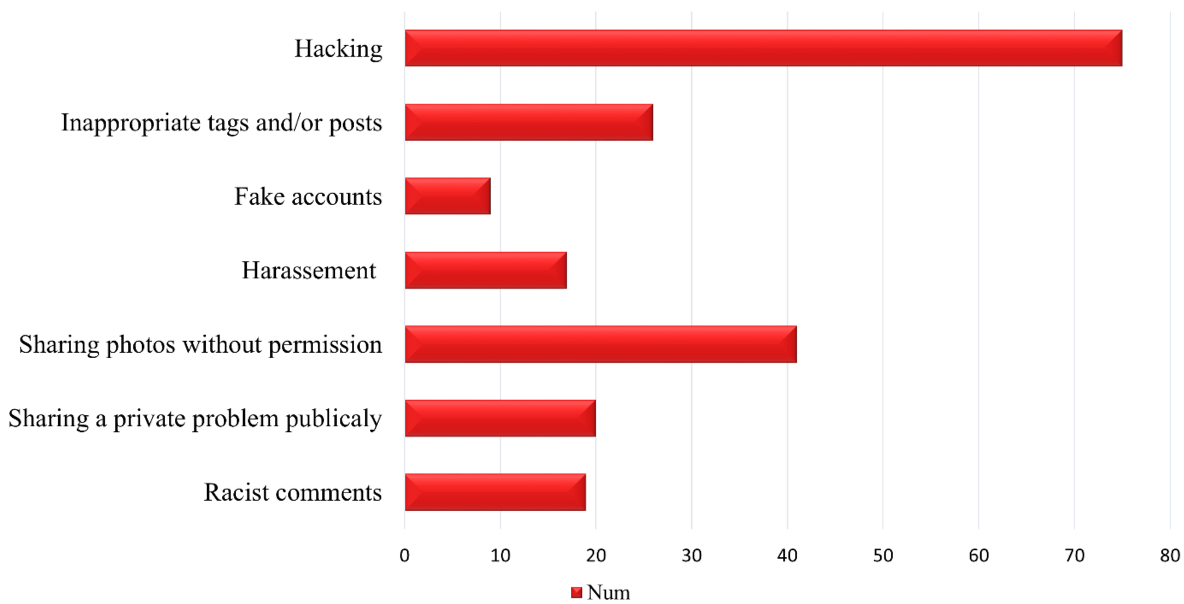


Figure 25. *Offensive behaviors*

4.3.2 Measurement model

4.3.2.1 Descriptive statistics

Table 9 presents descriptive statistics of the used constructs. The means range from 2.46 to 3.39, while the standard deviations range from 0.62 to 1.01, which indicates that the data is narrowly spread around the mean. Furthermore, skew and kurtosis indices were tested to ensure a good level of multivariate normality in the data for SEM [23]. The skew index of our data ranges from -0.99 to 0.35 (does not exceed |3|), and the kurtosis index ranges from -0.51 to 1.98 (does not exceed |10|).

Table 9. *Descriptive statistics of used constructs*

Constructs	Number of Items	Mean	S.D.	Skewness	Kurtosis
Facebook involvement	8	3.00	0.74	-0.06	0.09
Facebook Acceptance	13	2.96	1.01	-0.36	1.02
Empathy	5	3.26	0.62	-0.22	0.11
Commitment	4	3.93	0.97	-0.87	0.42
Pre-transgression trust	9	3.80	0.71	-0.99	1.98
Trust after the offense	9	2.78	0.92	0.06	-0.51
Forgiveness	10	2.46	0.93	0.35	-0.31
Severity	1	2.08	0.80	-0.15	-1.44

4.3.2.2 Convergent validity

Following Fornell and Larcker [151] procedures, the convergent validity of the measurement items was tested at three levels. The first tested indicator of convergent validity was the average variance extracted (AVE) for each construct, which should equal or exceed 0.50 [151]. As shown in **Table 10**, all AVE values are greater than 0.60, which meets the recommended guidelines. Moreover, the composite reliability (CR) of the constructs is recommended to be equal or greater than 0.70 to be adequate [151]. **Table 10** shows that all CR values are larger than 0.70, which is strongly acceptable. Consequently, the convergent validity for the used measurements in this study is adequate. Moreover, the results support the non-existence of multi-colinearity as all correlation values are below 0.7

4.3.2.3 Discriminant validity

We assessed discriminant validity by comparing the square root of the AVE for a given construct with the correlations between that construct and the other constructs, where the square roots of the AVEs should be greater than the corresponding off-diagonal elements for a construct

[151]. According to **Table 10**, the required discriminant validity of the measurement model is also satisfactory.

Table 10. *Convergent and discriminant validity of the constructs*

	CR[a]	*AVE*[b]	FA	FI	C	E	T	F
FA	***0.96***	***0.70***	**0.83**					
FI	***0.92***	***0.61***	0.60*	**0.78**				
C	***0.94***	***0.81***	0.36*	0.45*	**0.90**			
E	***0.83***	***0.63***	0.16*	0.19*	0.14*	**0.79**		
T	***0.94***	***0.64***	0.40*	0.40*	0.43*	0.28*	**0.80**	
F	***0.97***	***0.76***	0.10	-0.08	-0.11*	0.001	-0.14*	**0.87**

[a] Acceptable level at > .70 ; [b] Acceptable level at > .50 ; *p < 0.01

Table 11. *Data-model fit and Chi-square difference test for the modified model*

Recommended guidelines *	χ^2 *(df,p)*	χ^2 */df*	*GFI*	*CFI*	*IFI*	*TLI*	*RMSEA*
		<3	>0.90	>0.90	>0.90	>0.90	<0.08
Original Model	938.167 (246, < 0.001)	3.8	0.80	0.76	0.76	0.73	0.096
Modified Model	337.515 (193, < 0.001)	1.74	0.91	0.95	0.95	0.94	0.050
	$\Delta\chi^2 = \chi^2_{original} - \chi^2_{modified}$ = 938.167 – 337.515 = 600.652 (*df* = 53 , *p* < 0.001)						

* [153], [154]

4.3.3 Structural model

The analyses were conducted using the SEM approach with the **AMOS** software. To ensure that the proposed model describes the observed data, different model fit indices were tested (see **Table 11**). The goodness-of-fit indices of the original proposed model were weak; which means the model does not describe the observed data. Based on chi-square value and fit indices improvements, significant covariance structures between variables were added in the conceptual model (viz. {Commitment, Facebook acceptance},{ Commitment, Facebook involvement}, {Facebook involvement, Facebook acceptance}) using two-sided dashed arrows in **Figure 26**. Moreover, two direct paths were added in the structural model (viz. Empathy → Trust, Commitment → Trust) as shown in **Figure 26** with long-dashed arrows. This addition is theoretically supported, and it will be addressed in the discussion section. The fit indices of the modified model meet the guidelines, thus, the model is a good fit for the data.

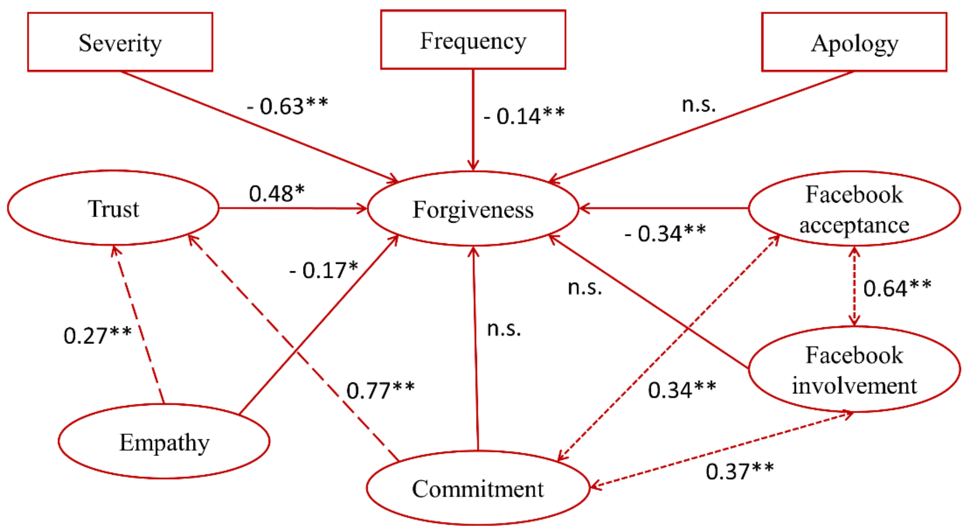


Figure 26. *Structural model*[14]

Table 12 summaries all the hypotheses and their validity. We examined path coefficients in the new structural model. Empathy is found to have a significant negative influence on Forgiveness (β = - 0.17, p<0.05), which contradicts our first hypothesis. Therefore, **H1** is not supported. In a similar way, Facebook acceptance has a significant negative influence on Forgiveness (β = - 0.34, p<0.01), so **H6** is not supported either. Surprisingly, commitment, apology and Facebook involvement have no significant effect on forgiveness; thus, **H2**, **H5** and **H7** are not supported. However, the severity of the offense and its frequency of occurrence have a direct significant negative influence on forgiveness (β = -0.63, p<0.01; β = -0.14, p<0.01, respectively). Consequently, **H3** and **H4** are supported. On the other hand, pre-transgression trust is also found to influence forgiveness positively (β = 0.48, p<0.05) which supports **H8**. Moreover, trust before

[14] (* p < 0.05, ** p < 0.01, n.s.: non-significant)

the offense is found to be strongly affected by both empathy and commitment (β = 0.27, p<0.01; β = 0.77, p<0.01). Thus, both added paths in the modified model are supported.

Table 12. *Regression weights for modified model*

	Causal path	β	S.E.	*z*-stat.	*P*	Std. β	Result
H1	Empathy →Forgiveness	-1.800	0.910	-1.978	0.04 *	-0.17	Not supported
H2	Commitment →Forgiveness	-1.213	1.374	-0.883	0.37	-0.16	Not supported
H3	Severity →Forgiveness	-5.805	0.457	-12.707	**	-0.63	Supported
H4	Frequency →Forgiveness	-2.013	0.720	-2.797	**	-0.14	Supported
H5	Apology →Forgiveness	1.089	0.722	1.510	0.13	0.07	Not supported
H6	Facebook acceptance → Forgiveness	-2.555	0.880	-2.902	**	-0.34	Not supported
H7	Facebook involvement → Forgiveness	1.375	0.883	1.557	0.12	0.16	Not supported
H8	Trust [a] →Forgiveness	1.138	0.522	2.179	0.02 *	0.48	Supported
	Empathy→Trust	1.223	0.258	4.749	**	0.27	Supported
	Commitment →Trust	2.492	0.190	13.104	**	0.77	Supported

* p < 0.05, ** p < 0.01.

4.3.4 Trust dynamic after the offense

A *paired t-test* was run on the sample to determine if there was a statistically significant mean difference between trust scores whether or not participants forgave the offender. There was a significant difference in participants' trust before the hypothetical offense (M = 3.80, SD = 0.71) and trust after it (M = 2.78, SD = 0.92) with 95% CI, $t(323)$ = 22.14, p < 0.001. However, participants' trust seems to decrease more when participants do not forgive (1.50 ± 0.90) than when they forgive the offender (0.83 ± 0.72). **Figure 27** illustrates trust means before and after the offense when participants forgave their offender and when they did not.

Focusing on trust differences when the participants forgave the offense, both aspects of trust decreased after the offense as shown in **Figure 28**, with a significant average difference between trusting belief before and after the offense ($t(236)$ = 16.58, p < 0.001), as well as between trust behavior scores ($t(236) = 14.77$, $p < 0.001$). However, trust decreases much more in the absence of forgiveness as shown in **Figure 29**.

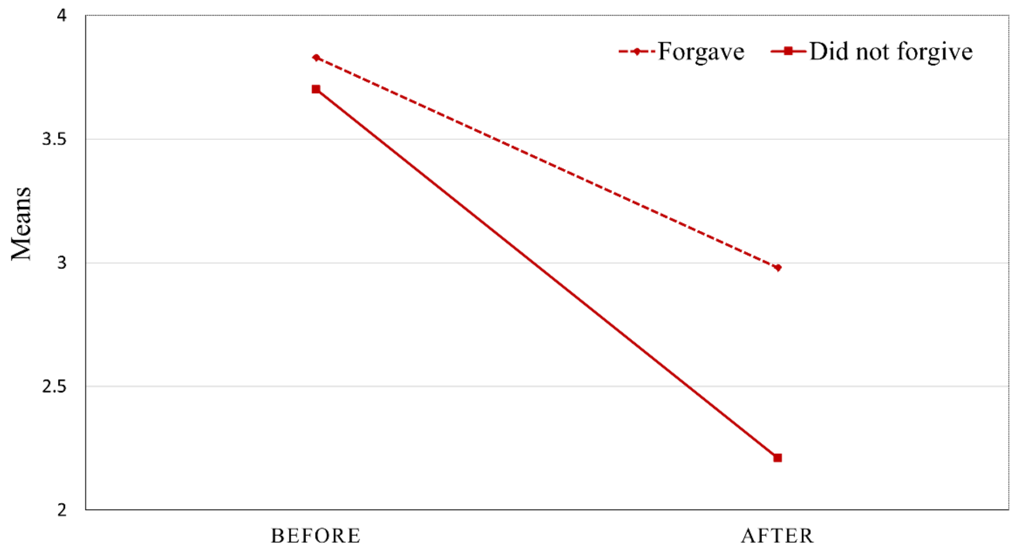


Figure 27. Trust before and after an offense

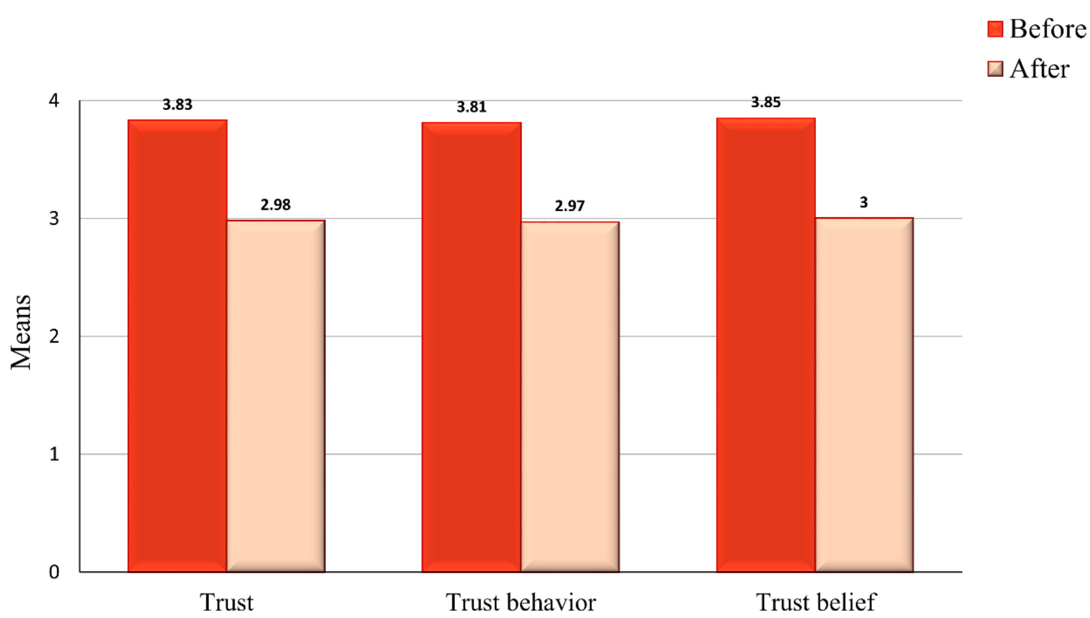


Figure 28. *Trust differences in the presence of forgiveness*

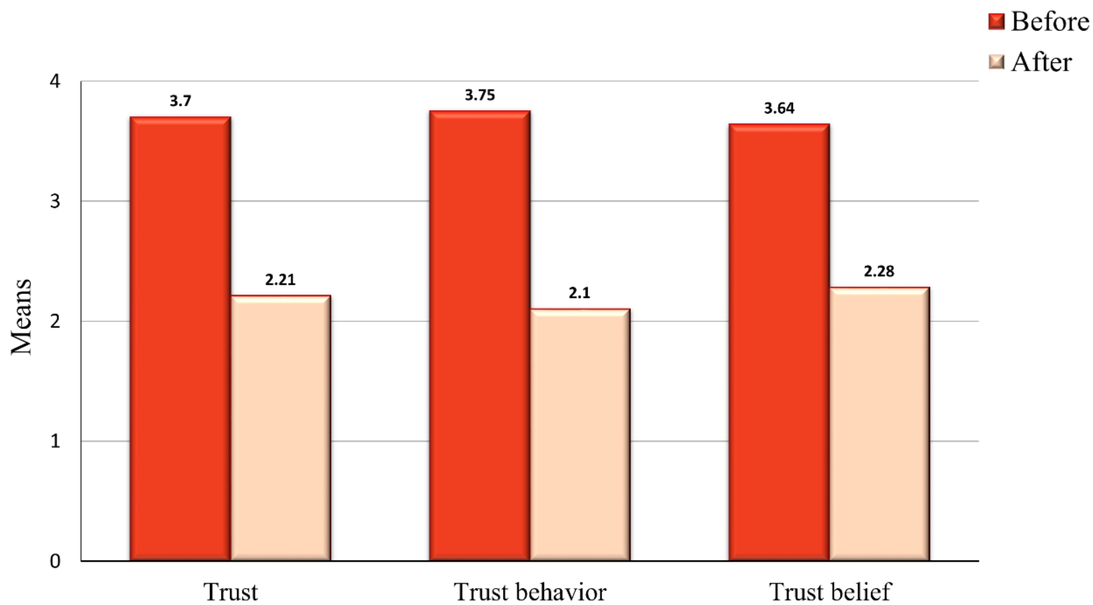


Figure 29. *Trust differences in the absence of forgiveness*

4.4 Discussion

Unlike in previously published results (e.g. [10], [92], [144]), our findings show that empathy does not have a significant *direct* positive impact on forgiveness in a digital environment. A possible explanation of this result is the fact that empathy is claimed to be weaker in the online world than in face-to-face interactions [155]. Although some research suggests that technology-based communications have a slender negative impact upon real-world empathy, virtual empathy scores were found to be much lower than real-word empathy scores and empathy in offline settings demonstrated stronger relationships than in online settings [156]. Some individuals may shift to cynicism, cruel criticisms, rude language, and cyber bullying as digital communications are deprived of many signals and reminders experienced in traditional communications (e.g., eye contact, body language), which can consequently decrease the expression of empathy in online communications [157]. Accordingly, empathy does not have a direct positive impact on forgiveness in online-related conflicts. However, empathy levels may vary according to the context and the online community [158], which requires further investigation.

In the same vein, our findings show that commitment has no significant influence on forgiveness, contradicting other studies such as [8], [98], [144]. According to [159] and [160], online social networks activities would decrease relationships satisfaction and commitment.

Unlike in offline relationships, commitment can be displayed publically through public interactions such as “liking” the friend’s posts and “sharing” pictures on each other’s Facebook wall. This public display of commitment can attract public criticism or approval of other friends, which may diminish commitment in online relationships.

In line with the literature, both severity and frequency of the offense are found to negatively affect forgiveness. The more severe and the more frequent the offense is, the less victims tend to forgive. Yet, the severity of transgressions is subjective and can be determined by many factors such as the relationship satisfaction, community standards, and culture.

While apology was considered to be a strong forgiveness predictor in many experiments conducted in offline settings, it did not influence forgiveness when the wrong deed is online-related. In order to be effective at improving a relationship after a conflict and increase forgiveness likelihood, apologies must be genuine and sincere. A sincere apology should contain many elements such as remorse, admission and taking responsibility of the wrongdoing, acknowledgment of harm, offering a repair and/ or an explanation [161], [162]. However, evaluating apology sincerity may require more factors which are hard to assess in digital settings, such as voice tone, non-verbal behavior, quality of the pre-existing relationship between the victim and the offender, as well as whether the apology was given right after the wrongdoing or much later [162].

While Facebook acceptance and involvement did not associate with forgiveness, pre-transgression trust turned out to have the second strongest impact on forgiveness in our model after the severity of the offense. As emphasized by Rusbult and his colleagues in [12], our findings indicate that trust associates positively with victims’ forgiveness. Moreover, both commitment and empathy positively relate to trust. A strong commitment boosts prosocial behaviors in a relationship, which enhances trust [163]. On the other hand, researchers from diverse fields claim that empathy has a significant impact on the formation of online interpersonal trust in different settings [164]–[167].

Finally, our data revealed that both victims’ trust belief and trusting behaviors towards their transgressors decline after the offense. However, trust decreased much more in the absence of forgiveness. Therefore, forgiveness is necessary to repair a broken relationship in online-related conflicts.

4.5 Summary

The main purpose of this chapter was to investigate the factors that can predict and promote forgiveness in a digital environment in an attempt to reanimate it and avail of its benefits. Drawing upon the existing literature about forgiveness in offline settings, we primarily proposed a research model and empirically tested it through a survey. Surprisingly, while empathy and commitment had no significant direct effect, results showed that the severity of the offense, its frequency and pre-transgression trust are the main factors that influence forgiveness. Moreover, a victim's trust towards the transgressor decreased much more in the absence of forgiveness than in its presence. The theoretical framework we have conducted and discussed so far highlighted how the main factors weigh on forgiveness decision in a linear mode. To operationalize the theory, a concrete model is needed, where ranges and weights of all the factors as well as the way they affect victims' decisions are defined. To this end, the significant variables will be used as inputs to develop forgiveness prediction models in the following chapter.

Chapter 5

Computational Model[15]

In this chapter, we will show a possible implementation of the theoretical forgiveness model developed in the previous chapter. This implementation uses a neural network model and a fuzzy approach. In particular, our attempt is to evaluate, using a specific implementation, the applicability of soft computing techniques in predicting forgiveness. In addition, simulation experiments were carried out using previously developed model, to call attention to the potential benefits of forgiveness in maintaining connectedness in a social network.

Motivation

SEM has been frequently applied in verifying hypothesized causal relationships in social and behavioral sciences where key variables of interest (latent constructs/ dependent variables) are observed indirectly through independent observations using questionnaires. However, SEM can only examine linear relationships between variables in a compensatory model, which assumes that the deficit in one of the factors can be compensated by improving other factors. For example, the high severity of the offense may be compensated by the victim's strong trust in the offender in order to forgive him/her. Nevertheless, the linear compensatory model may oversimplify the complications involved in victims' decision to forgive where forgiveness factors are entirely different and have different impacts on forgiveness. To overcome this issue, some researchers

[15] Parts of this chapter appear in the following paper:

- Laifa, M., Akrouf, S., & Maamri, R. (2018): Forgiveness and trust dynamics on social networks. Adaptive Behavior**,** *26*(2), pp. 65 – 83..

combined the SEM approach with artificial intelligence techniques such as artificial neural networks (ANN) and Fuzzy Logic System (FLS) [168]–[173].

Compared to regression techniques, ANN has the ability to identify the non-compensatory and non-linear complex relationships, and can produce more accurate predictions [174]. Consequently, ANN will be able to perform more accurate predictions between forgiveness factors and forgiveness decision. Besides that, as ANN can learn from data input new situations that were not taught before, the accuracy of prediction can be improved [175]. On the other hand, FLS has many benefits over both SEM and ANN. For example, FLS allows using natural language labels (e.g., "the offense is *very* severe") for representing real life situations. As a result, intervals can be used instead of exact values. In addition, social concepts (e.g., trust, forgiveness, empathy, commitment) are vague and imprecise. Fuzzy logic is designed to deal with ambiguity and uncertainty [176], which makes FLS suitable for our research. Further, fuzzy methods are simpler than ANN from a computational complexity point of view, whereby there is no need for a training phase if the rule sets are designed specifically for the study.

5.1 Forgiveness prediction model

5.1.1 ANN

Artificial neural networks (ANN) are inspired by the biological neural networks. An ANN is composed of many "neurons" that co-operate to perform a task or solve a problem such as optimization, feature extraction, pattern recognition, and prediction. The gained popularity of ANNs is due to their advantages over traditional techniques. For instance, ANNs are robust and can adapt to unknown situations, in addition to their learning and generalization abilities [174].

A neural network consists of a collection of neurons connected with each other by directed weighted connection. It is defined by a sorted triple (N,V,w), where N is a set of neurons, V a set of connections between neurons $\{(i,j)|i, j \in N\}$, and $w_{i,j}$ is the connecting weight between two neurons i and j. These weights can be implemented in a square weight matrix W or, optionally, in a weight vector with the row number of the matrix indicating where the connection begins, and the column number of the matrix indicating, which neuron is the target [177]. These weights are identified, updated and adjusted through a learning process.

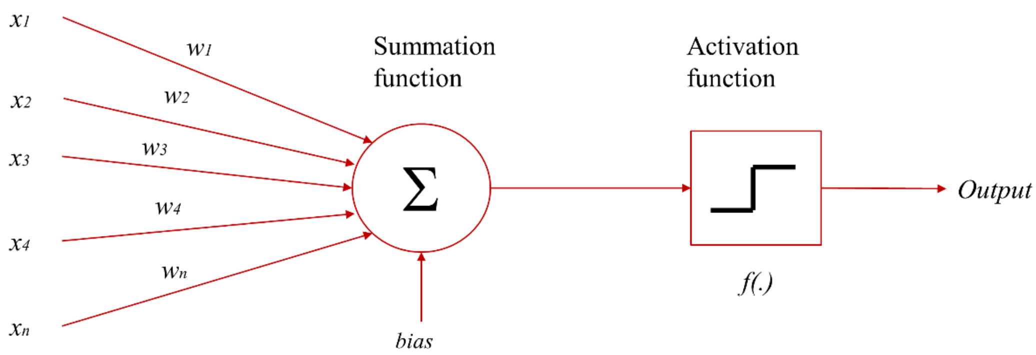


Figure 30. *McCulloch-Pitts model of a simple neuron [178]*

A very simplified model of neurons is the McCulloch-Pitts neuron [178] also known as *Threshold Logic Unit* (See **Figure 30**). The mathematical neuron computes a weighted sum of its n input signals x_i, $i = 1,2,\ldots.n$. The summation function is given as:

$$A = \left(\sum_{i=1}^{n} w_i x_i + bias\right)$$

Next, an *activation function* (also known as transfer/threshold function) is applied to the weighted sum of the inputs to produce an output [175], [178]. This function is chosen based on the problem that the neuron is solving, and it can be linear or nonlinear [177], [178]. A variety of transfer functions have been used where the most commonly used are the threshold function, piecewise linear, sigmoid, or hyperbolic tangent (see **Figure 31**). However, the sigmoid function is by far the most frequently used due to its smoothness and asymptotic properties. It is expressed mathematically as:

$$f(x) = \frac{1}{1 + e^{-n}}$$

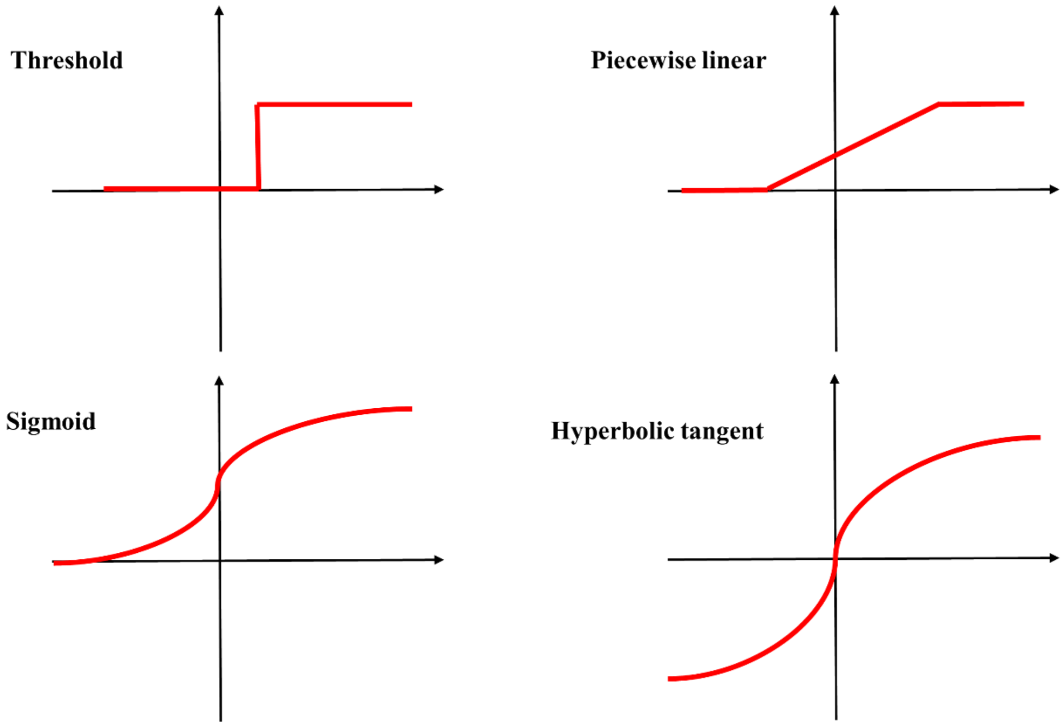


Figure 31. *Examples of different types of activation functions*

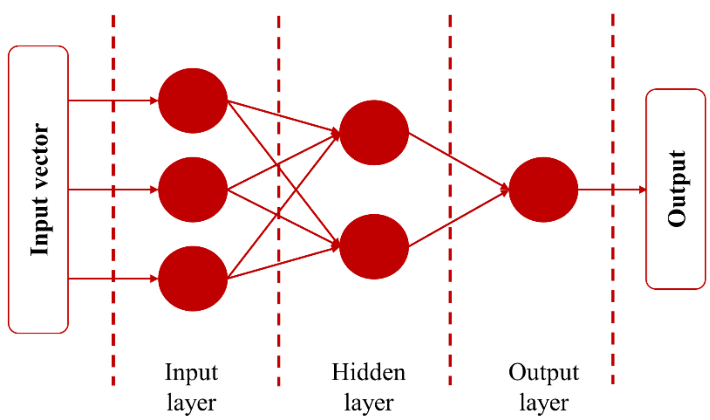


Figure 32. *Feed-forward topology of an artificial neural network*

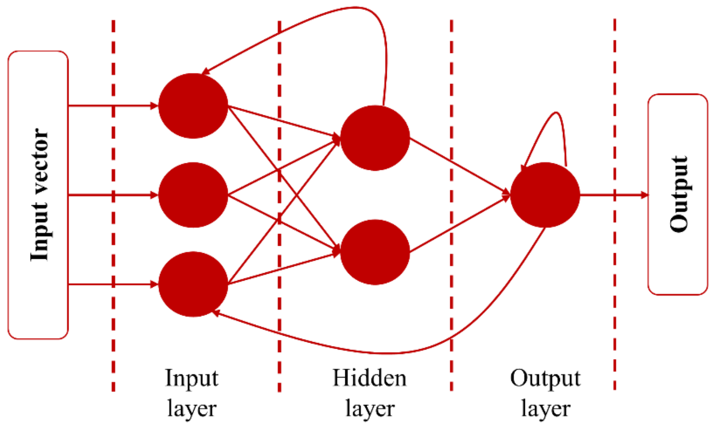


Figure 33. *Recurrent topology of an artificial neural network*

ANNs high computational capabilities require complex structure of the network, where many neurons are connected using two main topologies: *Feed-Forward* and *Feedback (Recurrent)*[174], [175], [177]. **Figure 32** and **Figure 33** show these two topologies. Note that for easier handling and mathematical describing of an ANN, individual neurons are grouped in separated layers: input layer, output layer, and one or more processing layers, which are called hidden layers. In Feed-Forward artificial neural network, information must flow from input to output in only one direction with no back-loops [179]. In the most common family of feed-forward networks, called multilayer perceptron, layers are clearly separated and connections are only permitted to neurons of the following layer [174], [179].

Figure 33 represents a simple recurrent topology. Recurrent ANN is similar to the Feedforward network but with no limitations regarding back-loops, where some of the information flows not only in one direction from input to output but also in opposite direction [174], [179]. Recurrent networks do not always have explicitly defined input or output neurons [177], [179].

As mentioned earlier, the most interesting characteristic of ANNs is their capability to *learn* automatically by training and, to be able to solve unknown problems of the same class. The learning process in the ANN context is viewed as the problem of updating the network architecture and connection weights so that the network can efficiently solve a specific problem. The connection weights are usually learned from available training patterns/datasets. There are three major learning paradigms; supervised learning, unsupervised learning and hybrid. Each learning paradigm has many training algorithms. The reader is referred to [174], [175], [177] for more details about different learning paradigms and their algorithms.

Table 13. *Performance variation of the ANN model with different number of neurons in the hidden layer*

	R		***RMSE***	
	Training	Testing	Training	Testing
NN1	0.8380	0.7681	0.4948	0.5784
NN2	0.8401	0.8104	0.4815	0.6085
NN3	0.8491	0.8226	0.5046	0.4887
NN4	0.8529	0.8266	0.4859	0.5372
NN5	0.7831	0.7607	0.6010	0.6460
NN6	0.8507	0.8376	0.4679	0.5391
NN7	0.8675	0.8052	0.4484	0.5503
NN8	0.8464	0.7804	0.4936	0.5514
Mean	**0.8410**	**0.8015**	**0.4972**	**0.5625**
S.D.	**0.0250**	**0.0285**	**0.0454**	**0.0481**

In this study, a multi-layer perceptron with a Feedforward-Back Propagation algorithm was used with three layers (i.e., input, hidden, output). The hidden and output layers applied the sigmoid function for activation. The input layer consisted of the four independent significant variables from the SEM analysis (i.e., trust, empathy, severity, frequency) while the output layer consisted of one output that is forgiveness. As there is no heuristic method for determining the number of hidden nodes in a neural network, this research followed [180] and [181] approach where the initial network was examined by including 4,6,8,10,12,14,16 and 18 hidden nodes. A network with 10 hidden nodes was then chosen as it was complex enough to map the used dataset while avoiding the over-fitting problem. **Table 13** shows the performance of the model according to the variation of the number of nodes in the hidden layer. The average cross-validation Root Mean Square Error (RMSE) for the training and testing model were 0.4972 (*S.D.* = 0.0454) and 0.5625 (*S.D.* = 0.0481) respectively. Thus, the proposed network model is reliable in capturing relations between the used inputs and outputs.

5.1.2 Fuzzy Logic

In Boolean logic (also called classical or binary logic), series of statements are either true or false (0 or 1). For example, objective statements such as '*the speed is 10km/h'* is either true or false in its specific context. However, subjective statements and answers like '*I trust him a lot'* are neither true nor false. This kind of statement depends on opinions, which diverge from person to person and from context to context. Fuzzy logic is an extension of Boolean logic by Lotfi Zadeh [182] based on the mathematical theory of ***fuzzy sets***, which is a generalization of the classical set theory.

Let X be a set. A fuzzy subset A of X is characterized by a ***membership function*** $f^{a} : X \rightarrow [0,1]$. $\mu_A(x)$ is called the ***membership degree*** of x in A. The concept of membership allows the definition of fuzzy systems in natural language by coupling fuzzy logic with linguistic variables. Fuzzy logic introduces the notion of degree of membership in the verification of statements to enable a statement to be in a state other than true or false. Therefore, FLS makes it possible to deal with inaccuracy and uncertainty, which provides a very valuable flexibility for reasoning. Another advantage of FLS is the use of rules in a natural language that is very close to human reasoning. Moreover, an FLS provides a transparent nonlinear mapping of inputs into a scalar output.

Let V be a variable (trust, empathy, etc.), X the range of values of the variable, and T_V a finite set of fuzzy sets. ***A linguistic variable*** corresponds to the triple (V,X,T_V). The proposed FIS for forgiveness prediction consists of four inputs: trust, empathy, severity of the offense and its frequency, where forgiveness is the output. For each variable, a fuzzy set is defined. Following the hypothetical scenarios and the scales we used to collect the data, the frequency fuzzy set of the offense will be defined as "once" and "many times", whereas the severity fuzzy set of an offense will be "extremely severe", "somewhat severe" and "not severe at all". Trust and empathy can be categorized as "low", "medium" and "high"; while forgiveness can be categorized as: "very low", "low", "medium", "high" and "very high". A fuzzy system has four components: fuzzy logic rules, fuzzifier, inference engine, and a defuzzifier (see **Figure 34**). Fuzzy reasoning is based on ***fuzzy rules*** derived from experiments and numerical data, or provided by experts. They are expressed in a natural language and presented as a collection of If-Then statements in the form:

Rule *i*: *IF* $x \in A_i$ *and* $y \in B_i$ *THEN* $z \in C_i$, where A, B and C are fuzzy sets.

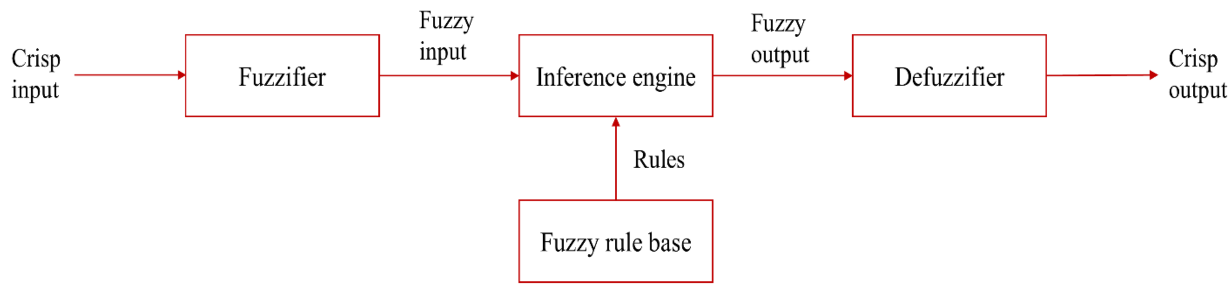


Figure 34. *Basic architecture of a fuzzy system*

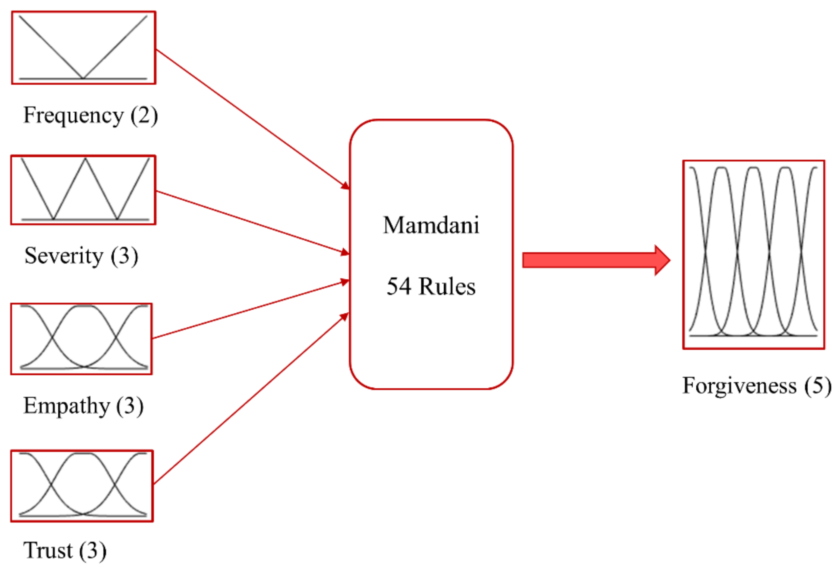


Figure 35. *Architecture of the used Mamdani fuzzy system*

Using ***membership functions***, the fuzzification process maps crisp input values into fuzzy sets to stimulate the fuzzy rules. The inference engine then determines the membership degree for each input and deals with combining those rules. Based on the defined fuzzy set for the output variables, the inference engine drives the output for each rule. These outputs are aggregated to form the final fuzzy output set. The output set is mapped as crisp numbers by the defuzzifier.

Among several existing inference methods, we follow the Mamdani min-max method [183]. Mamdani fuzzy inference system (FIS) is widely accepted for its intuitive nature and relatively simple structure [184]. In addition to the simplicity of interpretation and implementation, Mamdani can be used for systems with either single or multiple outputs [184]. A simple illustration of the used Mamdani model is illustrated in **Figure 35**.

To choose the suitable membership function form, we tried many membership function types for each variable and tested which reflects the case better. The Triangular-shaped membership function was chosen for Frequency and Severity inputs due to its simplicity as both inputs are not psychological concepts. The triangular curve is a function of a vector *x*, and depends on three scalar parameters *a*, *b*, and *c*, as given by:

$$f(x;a,b,c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases}$$

A two-sided Gaussian membership function was chosen for trust, empathy, and forgiveness due to its popularity, smoothness and being nonzero at all points. The function depends on four parameters σ_1, σ_2, c_1 and c_2 as given by:

$$f(x;\sigma,c) = \begin{cases} e^{\frac{-(x-c_1)^2}{2\sigma_1{}^2}} \\ e^{\frac{-(x-c_2)^2}{2\sigma_2{}^2}} \end{cases}$$

The first function, specified by σ_1 and c_1, determines the shape of the left-most curve. The second function specified by σ_2 and c_2 determines the shape of the right-most curve. Whenever $c_1 < c_2$, the two-sided Gaussian function reaches a maximum value of 1. Otherwise, the maximum value is less than one.

Figure 36 illustrates the inputs and output membership functions. The fuzzy system is then obtained by a collection of If-Then rules. According to the number of antecedent variables fuzzy subsets, 54 rules were reported (2×3×3×3). These used rules are stated in **Appendix E** as examples. Next, outputs for all rules are then aggregated and combined into a single fuzzy set using the *max* method. *Max* operator is the most common implementation of the rule aggregation step. It calculates the overall fuzzy output from the set of individual outputs taking the maximum truth value, where one or more terms overlap. The last step is the defuzzification, which results in a crisp output. There are any defuzzification methods such as the centroid, height, or maximum. In this work, we used the centroid method (also known as center of gravity method), as it is the most used and the most reliable. This method calculates the center of gravity of the surface obtained after the inference and the aggregation steps. More detailed information on the inference and defuzzification methods can be found in [184].

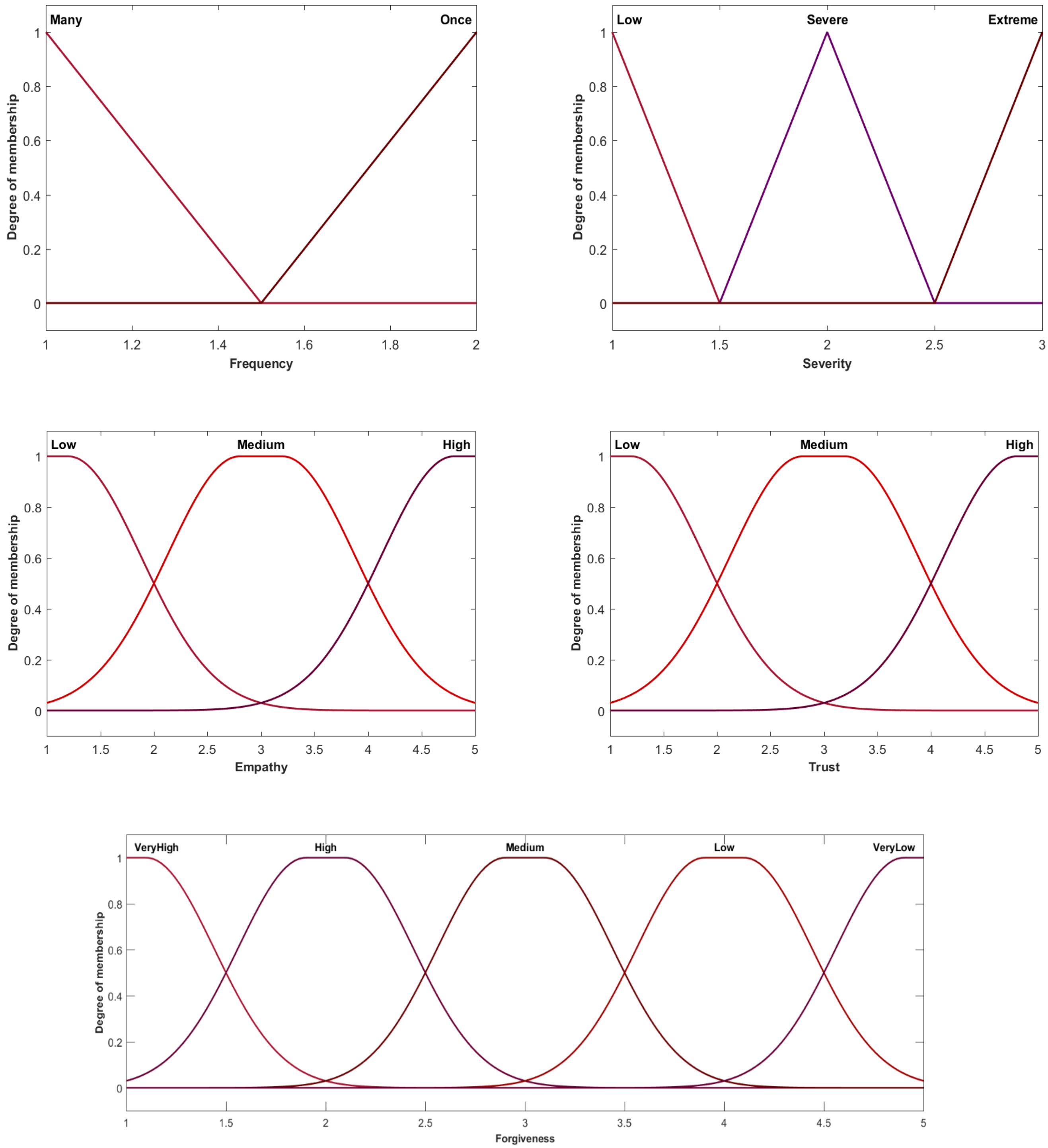


Figure 36. *The inputs and outputs membership functions*

Figure 37 illustrates a simplified example of the fuzzy inference system with only three rules, while **Figure 38**, **Figure 39** and **Figure 40** show the fuzzy inference system output surface with two variables.

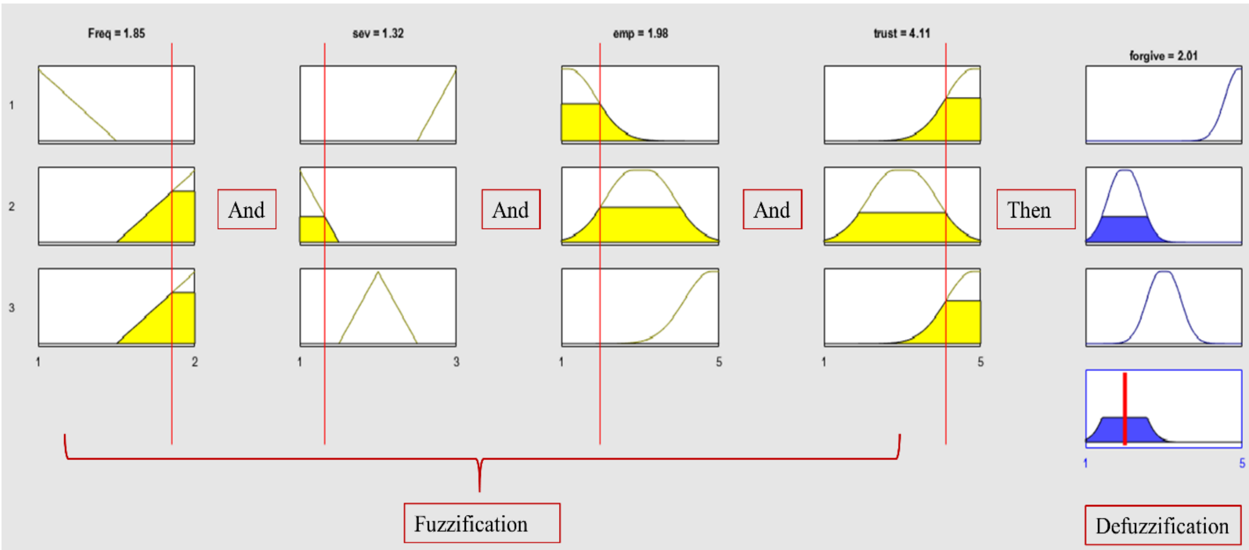


Figure 37. *Example of a fuzzy inference system*

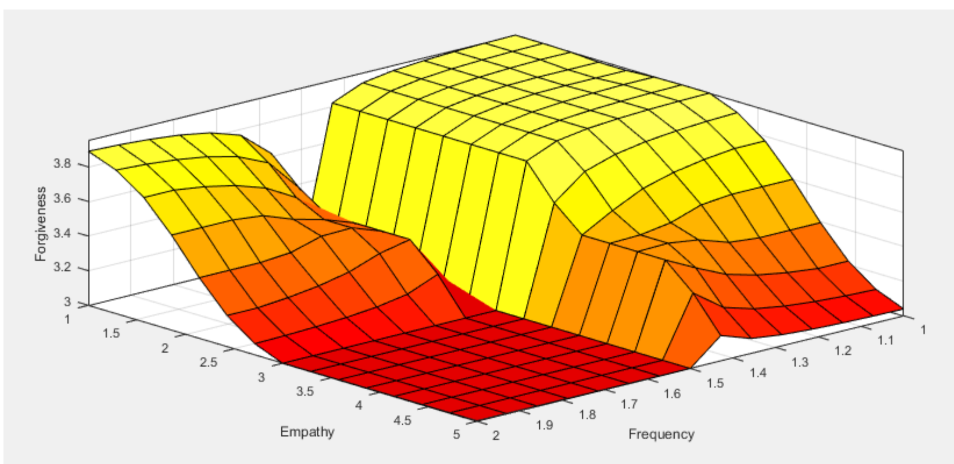


Figure 38. *Surface view with Empathy - Frequency*

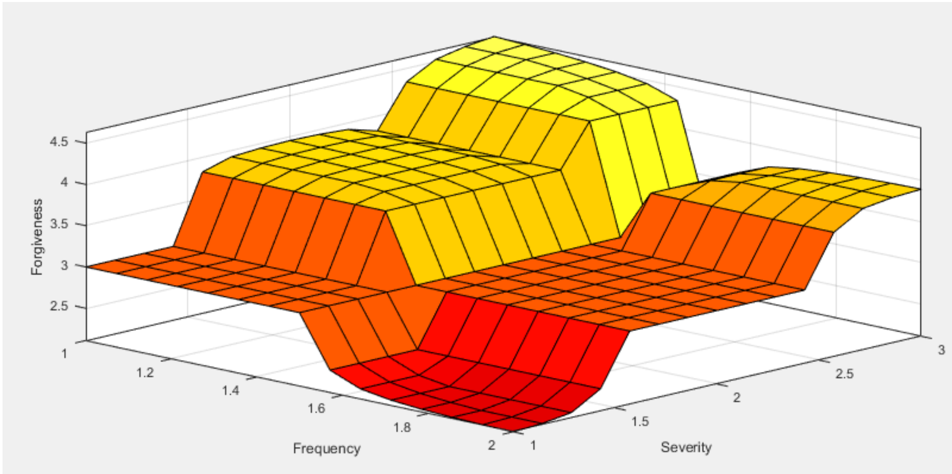


Figure 39. *Surface view with Severity - Frequency*

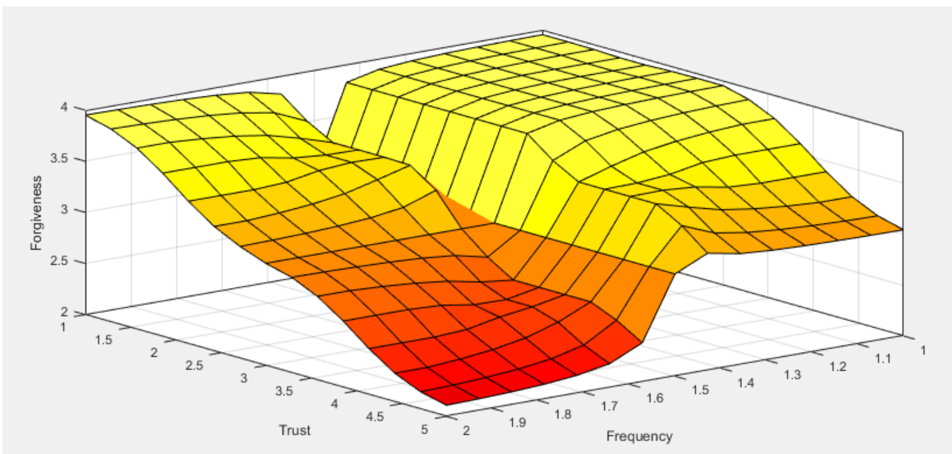


Figure 40. *Surface view with Trust - Frequency*

5.1.3 ANFIS

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the learning capabilities of neural networks and the reasoning of fuzzy logic, which enhances predictions. The main reason for using the ANFIS is to tune and adjust the input membership functions in order to minimize the estimated output error [185]. An ANFIS uses a Takagi-Sugeno type of inference system and a combination of backpropagation algorithm and least square methods along with the IF-Then rules. While Mamdani FIS outputs are part of the fuzzy set, Takagi-Sugeno FIS deals with the outputs as a mathematical function of a zero- or first-degree [186]. The rules therefore have the following form:

Rule *i*: *IF* $x = A_i$ *and* $y = B_i$ *THEN* $f = C_i$, where A and B are fuzzy sets, and C is a real value of rule i.

In this study, the previously presented Mamdani FIS was converted to a Takagi-Sugeno FIS. The architecture of the used ANFIS (shown in **Figure 41**) is explained below using only two inputs x, y, and one output z, for simplicity, and following [187].

Layer 1: Every node i in this layer is an adaptive node with a node function:

$O_{1,i} = \mu_{Ai}(x)$ and $O_{1,i} = \mu_{Bi}(y)$ and for $i = 1,2$

Where x and y are the inputs to node i and A_i, B_i are the linguistic labels (such as low, medium, high). In this layer, a two-sided Gaussian membership function was used, which can be represented as follows:

$\mu_{Ai}(x) = e^{\frac{-(x-c)^2}{2a^2}}$, where and c_i are *premise parameters*.

Layer 2: Every node in this layer is fixed and labeled Π, whose output is a product of all the incoming signals and represents the firing strength of a rule. The weight degree is:

$O_{2,i} = w_i = \mu_{Ai}(x) \, . \, \mu_{Bi}(y)$, for $i = 1,2$.

Layer 3: Every node is a fixed node labeled N. The normalized firing strength of each rule is computed in this layer. The outputs of this layer can be expressed as:

$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}$, for $i = 1,2$.

Layer 4: Every node in this layer is an adaptive node with a node function:

$O_{4,i} = \overline{w_i} f_i$, where $\overline{w}_i$ is the normalized firing strength from the previous layer.

Layer 5: the node in this layer is fixed and labeled as Σ, which computes the overall output as a summation of all incoming signals, as follows:

$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$

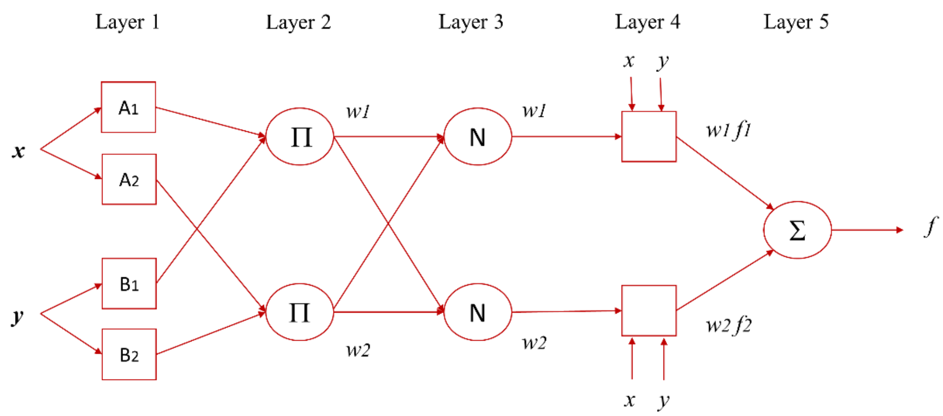


Figure 41. *The ANFIS architecture*

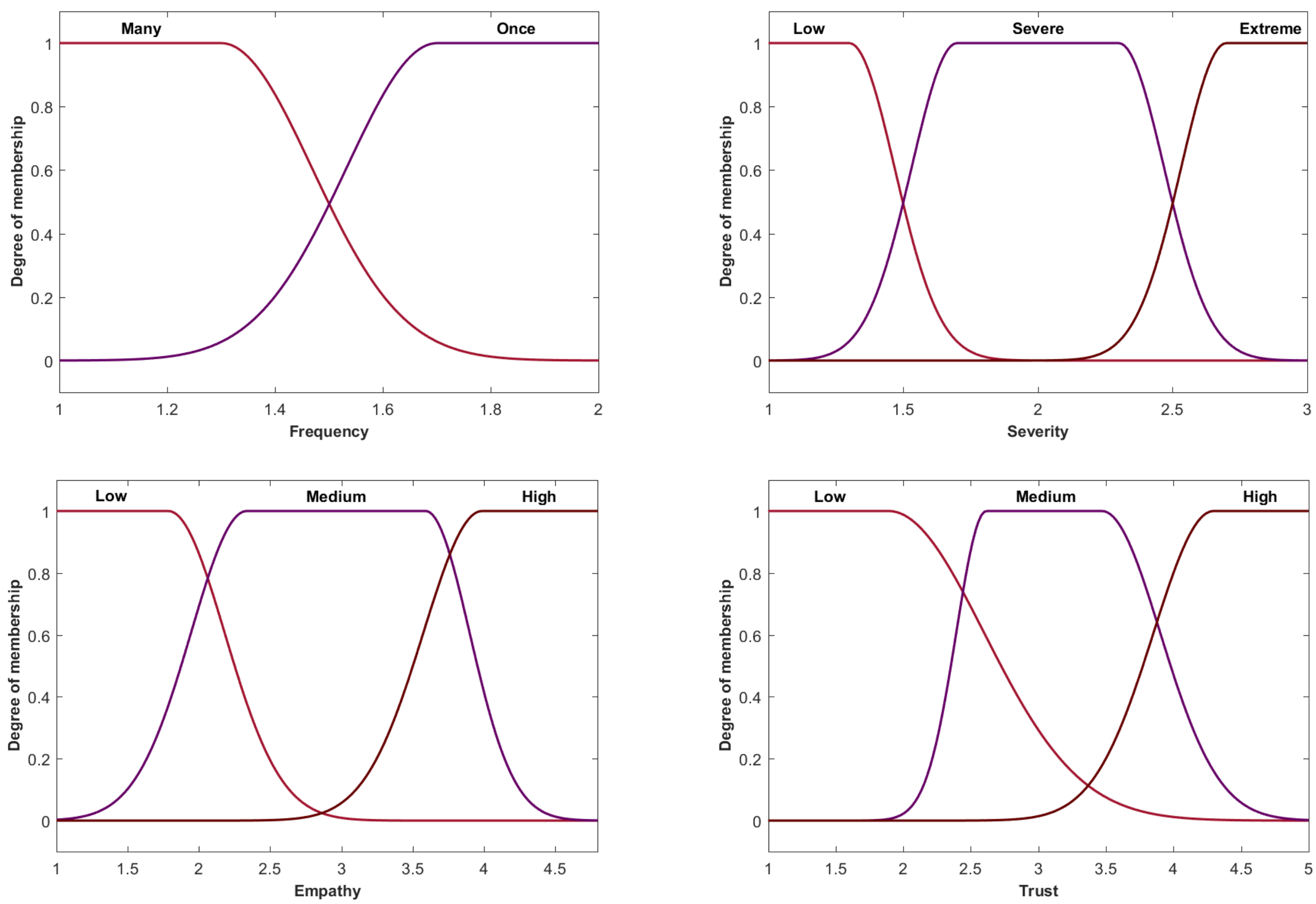


Figure 42. *Resulting membership functions after the training phase*

The same dataset used for training the previous ANN model was used to train and test the proposed ANFIS model. To evaluate the model, RMSE was calculated after each training session. Three Gaussian membership functions for each input parameter and the same 54 previously defined rules were used in the proposed model. **Figure 42** shows the resulting membership functions for the inputs.

5.1.4 Comparison

In this section, forgiveness prediction models' performance is compared. Four performance indices were chosen to evaluate the accuracy of those models and measure the variation of each one. These indices are: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) with the given equations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i' - y_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i' - y_i|}{n}$$

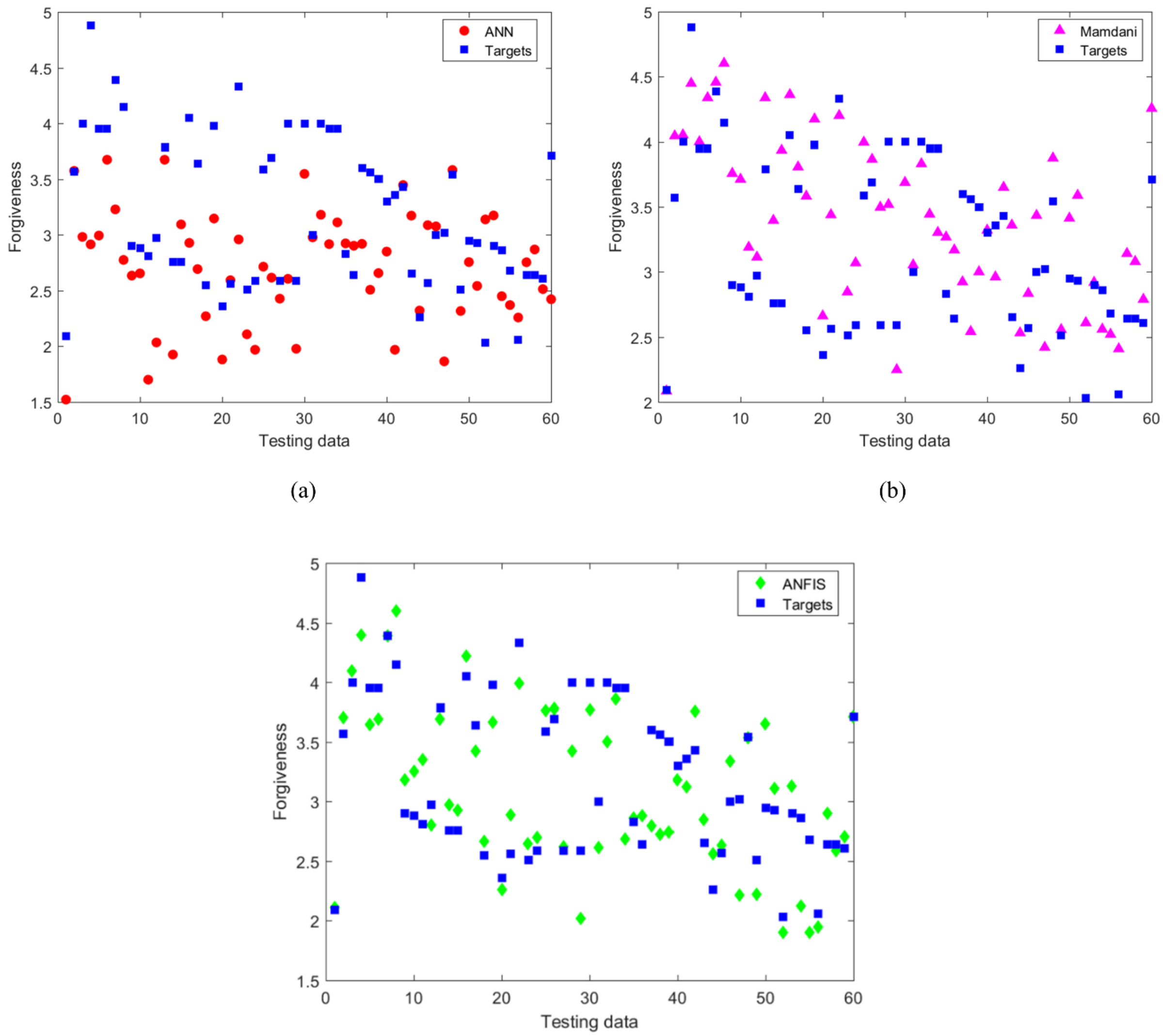
$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i' - y_i}{y_i}\right|$$

where y_i is the *i*th actual value from the dataset, and y_i' is the i^{th} predicted value. **Table 14** presents the resulting indices for each model using testing datasets.

Table 14. *Performance indices for ANN, Mamdani, and ANFIS models*

	MSE	*RMSE*	*MAE*	*MAPE*
ANN	0.3914	0.6256	0.5656	0.2713
Mamdani	0.2091	0.4573	0.3629	0.1447
ANFIS	0.0833	0.2886	0.2069	0.0863

As shown in the table, the Mamdani model performed better than the ANN model. However, the ANFIS model outperformed both the ANN and Mamdani models on the four indices. **Figure 43 (a)** highlights the poor performance of the ANN model. Hence, it is noticeable in **Figure 43 (b)** and **(c)** that Mamdani and ANFIS predictions were closer to the real values from testing data.



(a) (b) (c)

Figure 43. *Forgiveness prediction using testing data*

Results showed that Mamdani model performance was slightly better than the ANN model. This may be due to the ability of fuzzy logic to deal with uncertainties and ambiguity by captivating human perception through linguistic variables, which is very suitable for psychological concepts in particular [188], [189]. However, ANFIS outperformed both models. Similar to other studies in different fields, by combining FLS interpretability and ANN ability to learn and optimize fuzzy parameters, ANFIS provides more accurate predictions [185], [190]–[194].

5.2 Simulating trust dynamic

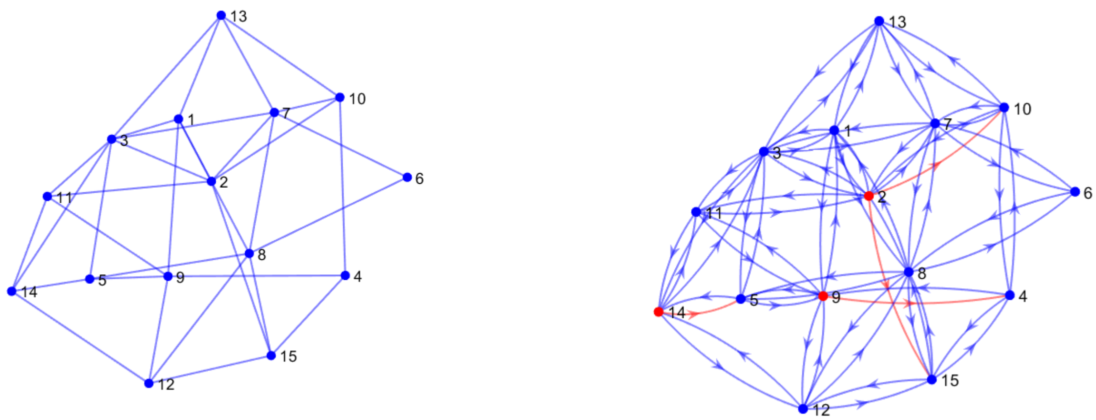
Depending on existing literature and the study objectives, we chose to employ agent-based simulation. Simulation has been broadly used to study a diversity of natural and social phenomenon [195]–[197]. A computational simulation for a social network enables the study of the consequences of different strategies, and helps to acquire insights into networks' patterns and characteristics at different levels. On the other hand, the dynamics of trust in a social network is hard to analyze because of the difficulties in observing its changes and obtaining the network data at different times. As looking at a static view of a network is not informative enough, we believe that a computational simulation is the adequate method to represent the effect of forgiveness on trust dynamic and how this latter can affect the structure of the simulated networks.

5.2.1 Experimental settings

For the purpose of our study, users are presented as agents and are embedded in a social network presented by a graph $G = (V_N,E_L)$ with $V = \{a_1, \ldots, a_N\}$ is a set of N agents, and $E=\{e_1,\ldots,e_L\}$ is a set of edges between agents. An undirected edge $e_{i,j}$ denotes that agents a_i and a_j are friends on the social network and they interact with each other. We used Erdös-Rényi graph model (aka Random Network model or ER for short). Due to its presentation simplicity, and ease to evaluate key network characteristics, ER network model was employed in a wide range of studies to reflect real world complex networks [198]–[202].

Following Gilbert [203], the random network is defined by the number of nodes N and the probability p that each pair of nodes is connected. The network is constructed then as follows. First, N isolated nodes are created. Next, for each selected pair of nodes, a random number between 0 and 1 is generated. If its generated number is greater than p then the two selected nodes are connected with a link, otherwise, they remain disconnected. This step is then repeated for each pair of nodes ($N(N-1)/2$ times). The density of the constructed network varies depending on N and p.

Given the fact that trust is subjective and asymmetric [28], [32], [33], the constructed network G is then converted to a directed graph $DG = (V_N,E_{2L})$ to distinguish the relationship characteristics (i.e., trust and empathy) between each two connected agents where random values in the range [1,5] were associated. Afterward, we assume that a specific number of offenses occurs in the network in each round of interaction. The offenses are assigned randomly and evaluated differently by the concerned agents, to reflect the subjectivity of offenses [97]. Frequency of the offense was also assessed for each offense occurrence. **Figure 44 (a)** shows a simplistic example of a generated undirected network with 15 nodes, while **Figure 44 (b)** shows the resulting directed network, and highlights four offenses (red arrows).



a

b

Figure 44. *A simplistic example of a generated network*

To assess trust dynamics after an offense for each interaction round, two different strategies were employed. In the first strategy, the network is updated by deleting the affected relationships without considering the relationships' characteristics nor forgiveness. In the second strategy, trust is assessed after the occurrence of an offense as follows:

$$T_A(a_i \to a_j) = T_B(a_i \to a_j) - \delta T_B(a_i \to a_j)$$

where T_A is trust value after the offense, T_B is trust value before the offense, and δ is a factor that reflects the change in trust values relating to the assessed forgiveness value with:

$$\delta = \begin{cases} 0\,, & no\ offense\ occured \\ 0.16\,, & F < 2.5 \\ 0.30\,, & F \geq 2.5 \end{cases}$$

where F is the assessed forgiveness value in the range [1,5], with 1 = strongly forgive, and 5 = strongly don't forgive (to follow the same scale used in while collecting data, see Section **4.2.1**). The ANFIS previously developed in **Section 5.1.3** is employed to predict forgiveness value. For more details about trust dynamics in the presence of forgiveness, we refer to Section **4.3.4**. The link between two agents a_i and a_j is deleted only if a_i trust in a_j or a_j trust in a_i after the offense is too low.

It is worth mentioning that we do not consider learning in the model's dynamic. We are just modeling the resulting effects that forgiveness may have on trust of a set of agents supposedly interacting, and the final evaluation of the network.

Table 15. *Networks characteristics*

	Small network		Large network	
	p = 0.05	p = 0.1	p = 0.05	p = 0.1
Average number of edges (L)	248	495	25041	49910
Average degree	4.98	9.83	50.50	100.308
Average betweenness	98.73	61.43	513.74	449.61
Density	0.049	0.099	0.0501	0.1002

5.2.2 Configuration

In order to implement the simulations properly, we set up a total of four experimental conditions (network size N, probability p, number of offenses x, and interaction rounds r) for which we ran 100 different simulations for each condition to establish a range of outcomes and to better assess the changes and reduce the noise. After comparing the results, we chose for the parameters that we found to reflect the study goal best. **Table 15** highlights average metrics of two networks to be used: a small network (10^2 nodes), and a large one (10^3 nodes). According to [204], [205] random networks usually follow a binominal distribution $P(k)$ of:

$$P(k) = \binom{N-1}{k} p^k (1-p)^{N-1-k}$$

where k is the nodes' degree (i.e., the number of links an agent has). The degree distribution of the generated networks are shown in **Figure 45**. **Table 16** summaries the used parameters for simulation. After each round of interaction, the original network is updated, and the average metrics are evaluated for comparison.

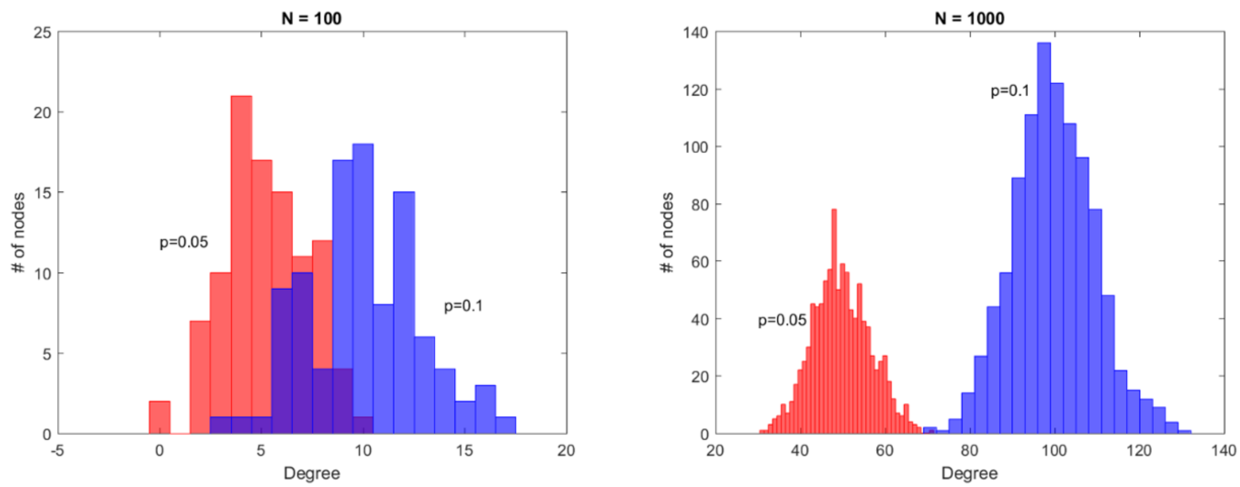


Figure 45. *Degree distributions of the generated networks*

5.2.3 Simulation results

Simulation experiments were carried out many times to reduce noise. Three metrics were assessed to compare the networks structure changes after revaluating trust with both forgiving and unforgiving strategies. These metrics are: average degree, average betweenness centrality, and density of the networks. **Figure 46** illustrates the average degrees for each network. It is noticeable that the average degree decreases for all the networks and with both strategies, which is expected as some of the relationships affected by the occurred offenses were deleted. In the first small network with $p = 0.05$ (**Figure 46 (a)**) and when forgiveness is not considered, the average degree decreases more when the number of offense x increases, until all agents are isolated after less than 20 rounds. However, the average degree does not reach 0 when forgiveness is taken into account when assessing the new trust values after the offenses. The same goes for the second small network with $p = 0.1$, where the diminution of connection between agents is slightly lower than the first network (see **Figure 46 (b)**).

On the other hand, large networks have a different changing pattern. For instance, for the first strategy in **Figure 46 (c)**, the average degree decreases from 50.50 to 49.10 after only three rounds with $x = 5$, then the drop is slender (red squares). A similar pattern occurs with the second strategy (green stars) where the average degree goes from 50.5 to 49.5 after 15 rounds, then the change is slender again. This patter may be caused by deleting important links (such as bridges). Likewise, in **Figure 46 (d)** it is prominent that the second strategy maintains and protects links between agents compared to the first strategy even with higher number of occurred offenses. When the number of links in a network decreases, density of the network (the level of interconnectedness) declines as well. **Figure 47** present the density of the networks after each round. Density of a network is the count of all the existing relationships between the agents divided by the total number of possible relationships. Most results show that the networks density lessens more for first strategy, where networks became very sparse, compared to the resulting networks from second strategy which they were relatively dense.

Table 16. *Summary of Experimental Parameters*

Name	Symbol	Range/value
Total interaction rounds	r	30
Number of agents	N	100, 1000
Probability of connecting	p	0.05 , 0.1
Number of offenses	x	5, 15, 25
Trust before the offense	T_B	[1,5]
Trust after the offense	T_A	[1,5]
Empathy	Em	[1,5]
Frequency	$Freq$	Once, many times
Severity	S	[1,3]
Forgiveness	F	[1,5]

Another general measure of centrality that we assessed was betweenness centrality. This metric focuses on the intermediating between any two agents in the network, which reflects the level of connectedness to other parts of the network. A higher betweenness centrality reflects more importance of edges for the structure of the network [205]. **Figure 48** shows oscillating curves for all the networks and with both strategies. Despite that, forgiveness strategy outperform unforgiving strategy by keeping the average betweenness of the network relatively high whether the number of occurred offenses is low (x = 5) or high (x =25).

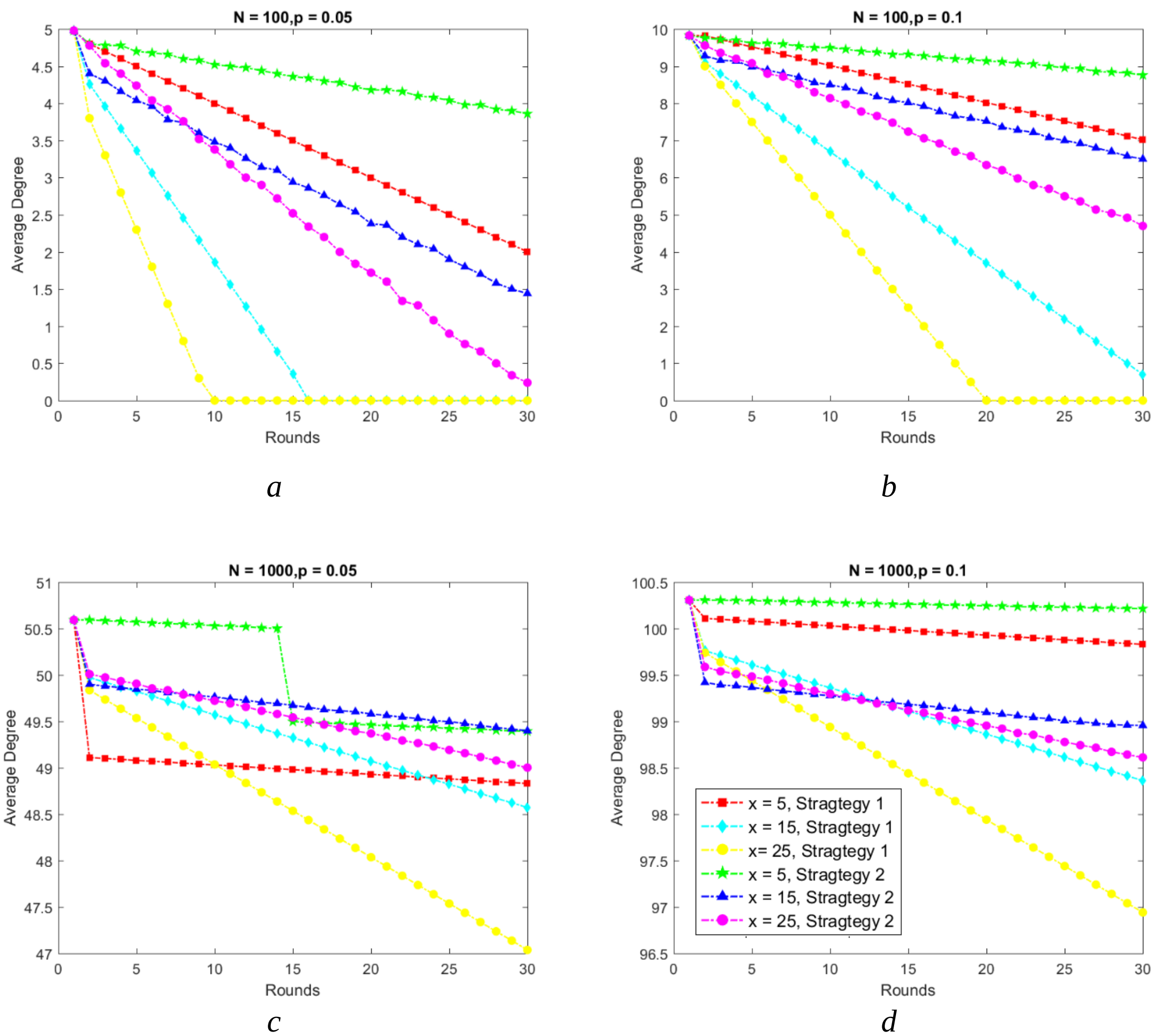


Figure 46. *Average degrees*

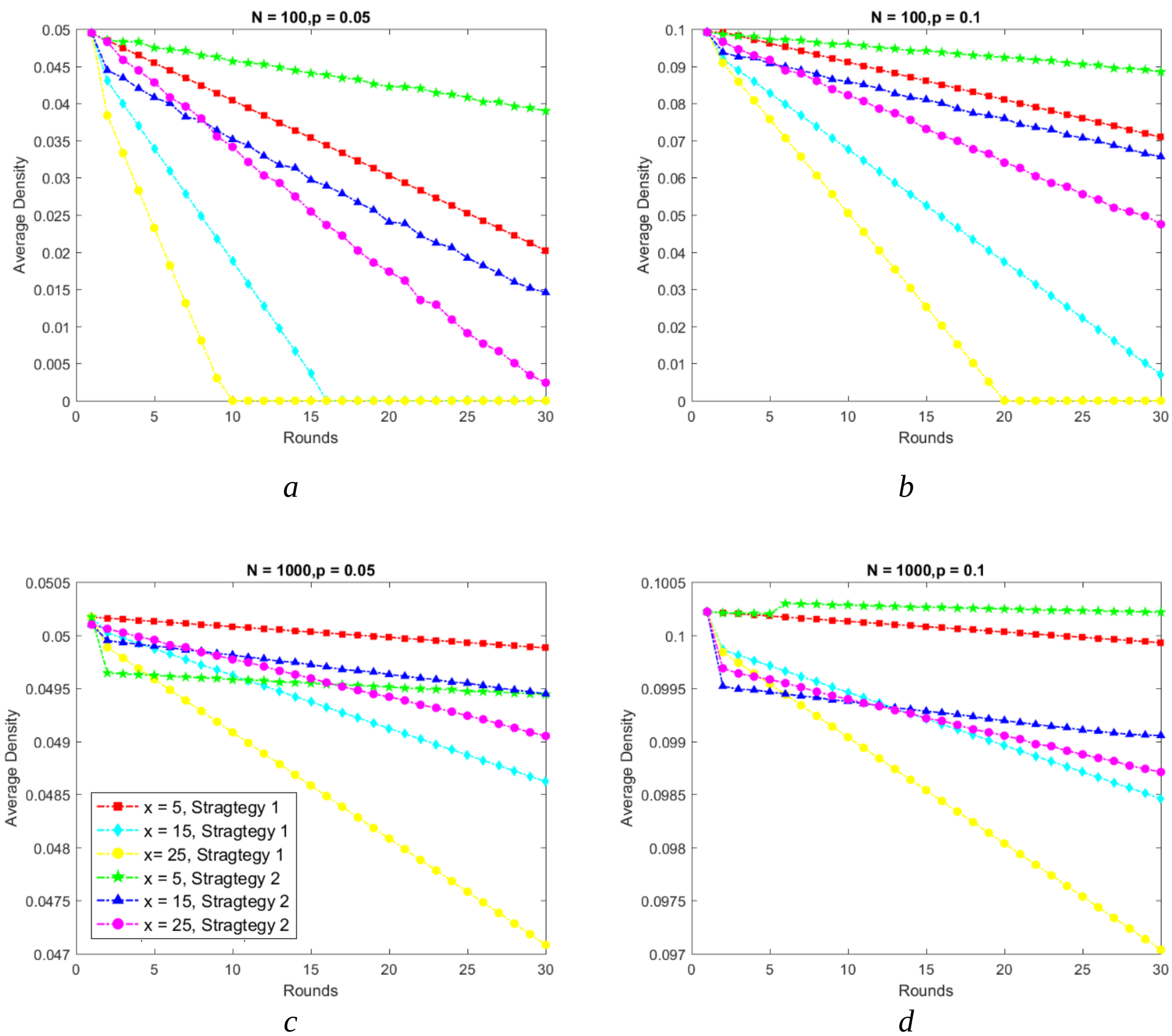


Figure 47. *Networks density*

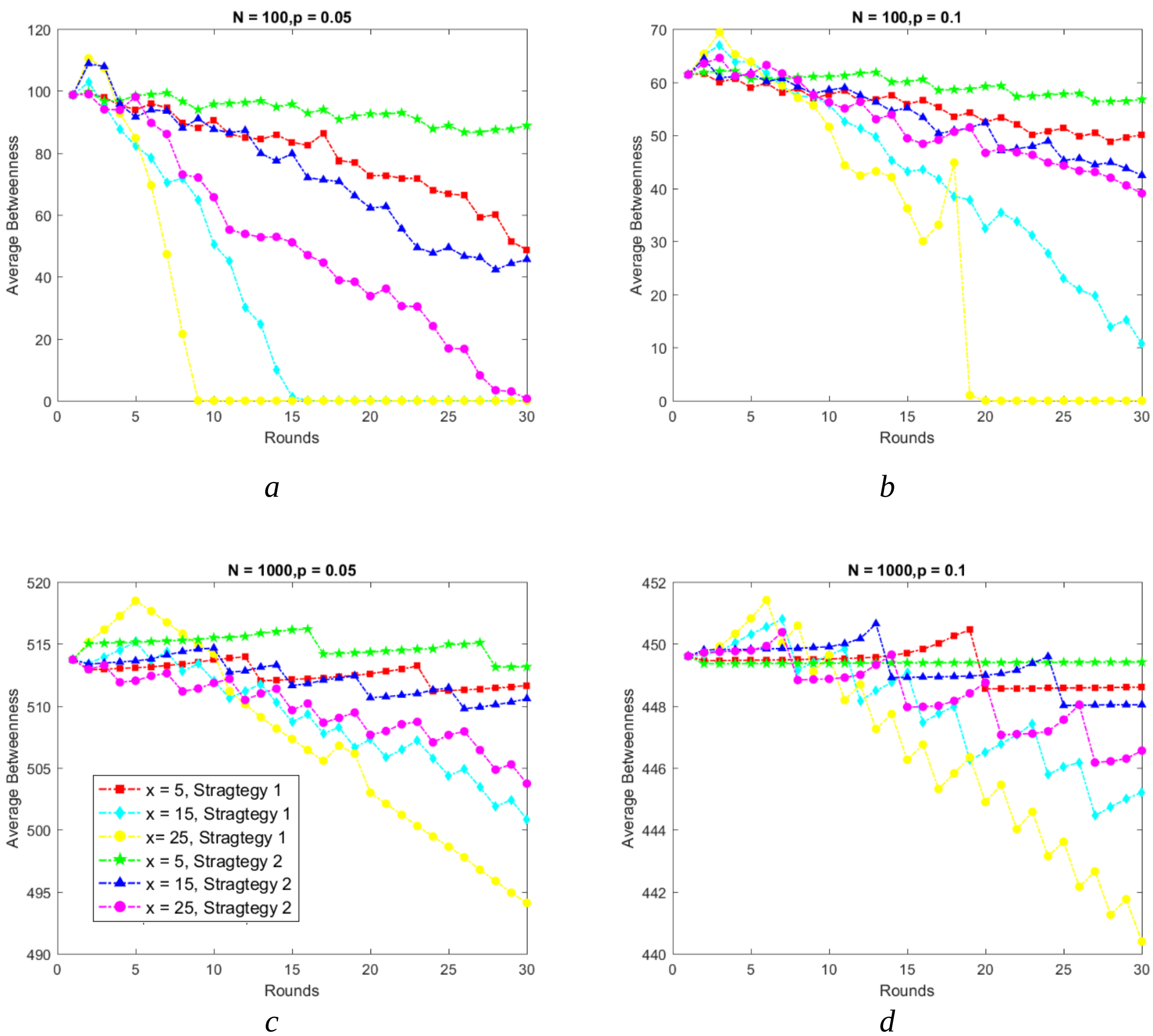


Figure 48. *Average betweenness centrality*

5.3 Summary

Two main AI approaches were used for forgiveness prediction: neural networks and fuzzy logic. SEM analysis permitted to select the input parameters with the maximum influence on forgiveness. Three models were developed: an ANN model, a Mamdani model, and an ANFIS model as a combination of the previous two models. The Performance comparison between the prediction models was conducted using MSE, RMSE, MAE, MAPE, where results showed that ANFIS outperformed other models.

The main purpose of this investigation was to evaluate the applicability of soft computing techniques on forgiveness prediction in an online social context. The models are not intended to be generalized due to contextual and cultural limitation of the input data used for developing those prediction models. Nonetheless, the preliminary analysis results of the potential of AI techniques for developing forgiveness prediction models can be extended to handle different contexts.

In this chapter, we also simulated trust dynamic after some offenses in a social network and how this can affect the structure of the network. Two strategies were employed: one that does not consider forgiveness, while the other takes into account forgiveness using the previously developed ANFIS model. In terms of centrality measures, the generated networks follow a pattern of decreasing. Nevertheless, networks centrality is maintained and relationships are preserved when forgiveness is considered.

Chapter 6

Conclusions and Implications

As individuals are having more access to the Internet and the number of hours they spend online is intensely increasing, social media became crucial tools in people's lives. Despite the positive impacts of social media, there are number of ways in which they can be used to cause more harm than good. People can easily be offended or hurt on social media due to privacy matters or cyberbullying, which can cause health issues (such as stress and anxiety) or lead to suicide - in some cases. Hence, trust and forgiveness are crucial to maintaining healthy relationships in a digital environment. In this dissertation, we contributed to some of the most fresh and exciting developments in this still thriving domain, namely the potential of trust and forgiveness for maintaining online relationships and connectedness. In the following sections, we summarize and evaluate the achieved goals of this research. Then, we address some challenges we faced during conducting different studies, and discuss some possible extensions of the current work and we propose future work that can overcome these limitations. Moreover, implications for both theory and practice of the presented work will be highlighted, followed by some closing thoughts about our experience during the years of conducting this work.

6.1 Summary and evaluation

In order to familiarize the reader of this dissertation to the work it covers, we first set the context that our project falls into and its relevance to computer science field. Next, we delineated our research settings and provided details about the process of collecting data that would be used trough out the present work. A brief description of the research procedure and the general outline of the dissertation were provided as well.

The earliest contribution of our research is providing an overview of online social trust, its properties and its metrics. We also provided a classification of the existing related work to this concept. In addition, we offered a presentation of forgiveness research basics such as its perceptions and factors. Likewise, Chapter 2 exhibited forgiveness related work in the digital environment as well as related issues to forgiveness studies that may face researchers interested in this topic.

Before moving to the main contributions of our work, we believed it was mandatory to dedicate some attention to the social media platform we chose, that is Facebook. As the participants in this research are Algerian students, we built upon previous investigations to examine their Facebook usage purposes, acceptance and involvement in using it. We also analyzed the relationship between their involvement in using and accepting of Facebook as a tool. Due to our limited scope, we did not dive into the benefits and efficiency of using Facebook as an educational context in Algerian universities. However, we believe that further research is indispensable in order to test the utility of such tools in education to overcome recent struggles and profit from their assistances.

The next contribution of our research was presented in Chapter 4 where factors that can predict and promote forgiveness in a digital environment were investigated in an attempt to reanimate forgiveness and avail of its benefits. We primarily proposed a theoretical framework and empirically tested it through the collected data. Surprisingly, while empathy and commitment had no significant direct effect, results showed that the severity of the offense, its frequency and pre-transgression trust are the main factors that influence forgiveness. Moreover, a victim's trust towards the transgressor was affected by forgiveness as it decreased much more in the absence of forgiveness than in its presence.

Finally, we illustrated a possible implementation of the developed theoretical forgiveness model. This implementation used artificial neural networks and fuzzy logic approaches. The main purpose of this contribution was to evaluate the applicability of soft computing techniques on forgiveness prediction in an online social context. The models are not intended to be generalized due to contextual and cultural limitation of the input data used for developing those prediction models. Nonetheless, the preliminary analysis results of the potential of AI techniques for developing forgiveness prediction models can be extended to handle different contexts. Further, simulation experiments were carried out using previously developed model, to call attention to the potential benefits of forgiveness in maintaining connectedness in a social network.

6.2 Limitations, challenges and future work

As the present study is one of the first studies that directly examine interpersonal trust and forgiveness in an online-related context, we believe our findings make significant contributions to the current literature on both concepts by providing the basic steps toward a better understating of the complicated process of forgiving in the digital environment and its impact on trust. At the same time, we should address some limitations of this work.

Our study relied only on two hypothetical offenses with different factors. Even though many previous studies used hypothetical scenarios, it is still debated that they can influence findings. Therefore, we acknowledge that further investigation is required, for instance by considering real offenses that happened to participants in the digital environment either by recalling a recent conflict or by having members interact through a specific digital platform for a period of time. On the other hand, a longitudinal design for observing online interpersonal relationships allows researchers to have better insight on the quality of pre-existing relationship before the conflict occurrence that might have an influence on victims' decision to forgive.

Furthermore, our sample focused on members of an Algerian culture. Cultural variation may have a direct or an indirect impact in a victim's decision to forgive. Thus, future research should consider a larger and more diverse sample and/or take cultural considerations into account. Likewise, the study can be extended by including more variables excluded in this study such as personality factors. Additionally, risk assessment is needed to be incorporated with forgiveness models to assure robustness.

Another limitation of our work is not considering the network dynamics over time to reflect real world social networks dynamics (growth, death, geographical movement, etc.). On the other hand, a trust prediction model can be developed to fit other contexts and to bring the simulation closer to reality. This may be possible through using more effective data collection methods other than surveys, especially to depict network evolvement over time.

As our main goal is to reanimate interpersonal forgiveness in a digital world to enhance user experiences and maintain online relationships, we believe that a vital strength of the current study is the prospect for related future research as well as the potential for applications. This investigation opens doors to more studies on forgiveness prediction using more sophisticated prediction models in order to be used by researchers or practitioners who are interested in forgiveness benefits. We are hopeful that confirmation of the significance of interpersonal forgiveness will encourage researchers to explore new techniques to facilitate it.

6.3 Theoretical and practical implications

Based on the theoretical arguments as well as the empirical results presented in previous chapters, this section will highlight some implications for both theory and practice. While most online trust research discussions center around models and approaches for building, evaluating and maintaining users' trust, our work focuses on the idea of repairing a broken one.

Reputation systems are a good example of a widely used approach to sustain trust relationships in an online social framework. In such systems, a victim of an offense attributes a bad/low feedback or rating to the offender. This bad feedback would be public to the community. However this kind of reputation systems do not consider unintentional offenses. Repairing trust in such cases will prevent negative and vengeful behaviors. This can be achieved by designing reputation systems that incorporate forgiveness mechanisms when appropriate. For example, a seller on Amazon may miss the delivery date due to some troubles on the post office side – that sellers cannot control. The delay may have serious consequences for the buyer which would result in an unintentional offense. Incorporating a forgiveness mechanism would give another chance for the seller to repair the buyer trust instead of causing a lasting damage.

Similarly, a trust-forgiveness approach can be implied in a social recommender system. Most social media platforms recommend friends and followers for users. While predicting friendships that would appeal to users is widely addressed, maintaining these friendships is tricky. Rather than focusing on users similarities alone, social recommender systems designers can improve users experience by ensuring that these friendships would last and not cause stress or harm. This can be achieved by encouraging forgiving unintentional harmful deeds made by trustful friends.

Clashing social dynamics often emerge from social and cultural differences. The advances of modern society on a technological level made it much harder to deal with this clashing. On a local scale, Algerian multicultural diversion is facing integration problems following the lead of developed countries such Europeans, serious computer games and simulations can promote intercultural communications and embody different perceptions on social issues. Such games comprise conflicts between the player and non-human players or other human players, and they are designed specifically to vanquish struggles in collaboration by rewarding winning by means of non-violent problem-solving approaches. Trust-forgiveness approach can be implied in such games to learn to solve communication conflicts, which would improve collaborations on a digital globalization age.

Likewise, on an educational level, introducing forgiveness mechanisms in E-learning platforms should be tested and examined in order to ease collaborations between students, and improve their experiences. This may be particularly helpful for student with learning difficulties especially in children (e.g., Auditory Processing Disorder, Dyscalculia, Dysgraphia, Dyslexia, Language Processing Disorder, Non-Verbal Learning Disabilities), to whom group work is a daunting task.

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Appendices

Appendix A

Anonymous Survey Consent

We are conducting a research project on users' experiences on **Facebook**. We'd love to hear from you about it. This will help us improve our research. We would appreciate your taking the time to complete the following survey. It should take about 10-15 minutes of your time.

Your responses will remain **strictly confidential**, and they will be used **only** for the academic research; they will **not be shared**. All responses will be compiled together and analyzed as a group. You can only take the survey **once**. All questions are **required**. Please read **carefully** the instructions before each question. The survey is available in **English** and **Arabic.**

If you have any questions, concerns or comments about the survey, please email us at: laifa.meriem@yahoo.fr

We value your honest and detailed responses.

Appendix B

Survey 1

Do you have internet access at home?	Yes	No
Do you have a Facebook account?	Yes	No

What do you use Facebook for? *(Please give at least 3 purposes)*

1. ……………………………………………………………………………………………………..
2. ……………………………………………………………………………………………………..
3. ……………………………………………………………………………………………………..
4. ……………………………………………………………………………………………………..
5. ……………………………………………………………………………………………………..

What are your usual activities with friends you trust on Facebook?

1. ……………………………………………………………………
2. ……………………………………………………………………
3. ……………………………………………………………………
4. ……………………………………………………………………
5. ……………………………………………………………………
6. ……………………………………………………………………
7. ……………………………………………………………………

What are the activities and behaviors you consider to be offensive and hurtf
transgressions even if they didn't happen to you personally)

1. ……………………………………………………………………
2. ……………………………………………………………………
3. ……………………………………………………………………
4. ……………………………………………………………………
5. ……………………………………………………………………
6. ……………………………………………………………………

What is your gender ?	Male	Female
What is your age?	Under 18 18 25 31 older than 40	 24 30 40
Are you …?	Married Divorced Widowed In a relationship Single	
What is your highest degree or year of school?	Freshman 2nd year	

	3rd year Master 1 Master 2 Doctorate degree
Which language do you use the most in your online communications?	Arabic French English Spanish Others

Please describe your feelings about the following statements

Using Facebook improves my work	1	2	3	4	5
Using Facebook enhances my effectiveness	1	2	3	4	5
Using Facebook increases my productivity	1	2	3	4	5
My interaction with Facebook is clear and understandable	1	2	3	4	5
I find Facebook easy to use	1	2	3	4	5
Facebook makes life more interesting	1	2	3	4	5
Working with Facebook is fun	1	2	3	4	5
I like using Facebook	1	2	3	4	5
I look forward to those aspects of my life that require me to use Facebook	1	2	3	4	5
When I need help to use Facebook, guidance is available to me	1	2	3	4	5
When I need to use Facebook, a specific person is available to provide assistance	1	2	3	4	5
People whose opinions I value encourage me to use Facebook	1	2	3	4	5
People who are important to me support me to use Facebook	1	2	3	4	5
I will use Facebook in the Future	1	2	3	4	5
I plan to use Facebook often	1	2	3	4	5

In a NORMAL DAY, how much TOTAL TIME do you spend on Facebook?	Less than 20 minutes 20 minutes - 40 minutes 40 minutes- 1hour 1 hour - 2 hours More than 2 hours	
What is the TOTAL number of Friends you currently have on Facebook?	Less than 100 100 - 200 200 - 300 300 - 400 More than 400	
Among your friends on Facebook, do you have		
Family members	Yes	No
Students from BBA university	Yes	No
Students at other universities	Yes	No

Professors, instructors or staff from BBA university	Yes	No
Professors, instructors or staff from other universities	Yes	No

Please describe your feelings about the following statements

Facebook is important to my university experience	1	2	3	4	5
Facebook is a part of my everyday activity	1	2	3	4	5
I am proud to tell people I am on Facebook	1	2	3	4	5
I feel out of touch when I haven't logged onto Facebook for a while	1	2	3	4	5
I feel I am a part of the Facebook community	1	2	3	4	5
I would be sorry if Facebook shuts down	1	2	3	4	5

Please bring to mind a Facebook friend who offended you online. Recall your relationship with this friend before the transgression, then describe your feelings about the following statements.
1: Strongly disagree 2 : Strongly agree

I believed that:					
He/she would act in my best interest.	1	2	3	4	5
If I required help, he/she would do its best to help me.	1	2	3	4	5
He/she was interested in my well-being, not just his/her own.	1	2	3	4	5
He/she was truthful in his/her dealing with me.	1	2	3	4	5
I would characterize him/her as honest.	1	2	3	4	5
He/she was sincere and genuine.	1	2	3	4	5
I used to:					
Like his/her posts.	1	2	3	4	5
Share posts with him/her.	1	2	3	4	5
Exchange private messages with him/her.	1	2	3	4	5
Visit his/her profile page to check for his/her news.	1	2	3	4	5

How severe was the offense for you? 1: not very serious 5: very serious offense	1	2	3	4	5

How frequent did your friend commit this offense? 1: once 2: twice …. 5: five time or more	1	2	3	4	5

Did your friend apologize to you?	Yes	No

Please describe your feelings about the following statements AFTER THE OFFENSE
1: Strongly disagree 5: Strongly agree

I wish that something bad would happen to him/her	1	2	3	4	5
I want him/her to get what he/she deserves	1	2	3	4	5
I want to see him/her hurt and miserable	1	2	3	4	5

I'll make him/her pay	1	2	3	4	5
I'm going to get even	1	2	3	4	5
I cut off the relationship with him/her	1	2	3	4	5
I live as if he/she doesn't exist, isn't around	1	2	3	4	5
I keep as much distance between us as possible	1	2	3	4	5
I find it difficult to act warmly toward him/her	1	2	3	4	5
I don't trust him/her	1	2	3	4	5
I withdraw from him/her	1	2	3	4	5
I avoid him/her	1	2	3	4	5

I believed that:

He/she would act in my best interest.	1	2	3	4	5
If I required help, he/she would do its best to help me.	1	2	3	4	5
He/she is interested in my well-being, not just his/her own.	1	2	3	4	5
He/she is truthful in his/her dealing with me.	1	2	3	4	5
I would characterize him/her as honest.	1	2	3	4	5
He/she is sincere and genuine.	1	2	3	4	5
I still :					
Like his/her posts.	1	2	3	4	5
Share posts with him/her.	1	2	3	4	5
Exchange private messages with him/her.	1	2	3	4	5
Visit his/her profile page to check for his/her news.	1	2	3	4	5

I want my relationship with him/her to last for a very long time	1	2	3	4	5
I am committed to maintaining my relationship with him/her	1	2	3	4	5
I would not feel very upset if our relationship were to end in the near future	1	2	3	4	5
I feel very attached to our relationship-very strongly linked to him/her.	1	2	3	4	5
I want our relationship to last forever	1	2	3	4	5
Our relationship is likely to end in the near future	1	2	3	4	5

I find it easy to put myself in somebody else's shoes	1	2	3	4	5
I am good at predicting how someone will feel	1	2	3	4	5
I am quick to spot when someone in a group is feeling awkward or uncomfortable	1	2	3	4	5
Other people tell me I am good at understanding how they are feeling and what they are thinking.	1	2	3	4	5

I find it hard to know what to do in a social situation	1	2	3	4	5
I often find it hard to judge if something is rude or polite	1	2	3	4	5
It is hard for me to see why some things upset people so much	1	2	3	4	5
Other people often say that I am insensitive, though I don't always see why	1	2	3	4	5

Appendix C

Survey 2

1. Please, describe your feelings about the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Using Facebook enhances my effectiveness					
Using Facebook increases my productivity					
My interaction with Facebook is clear and understandable					
I find Facebook easy to use					
Facebook makes life more interesting					
Working with Facebook is fun					
I like using Facebook					
When I need help to use Facebook, guidance is available to me					
When I need to use Facebook, a specific person is available to provide assistance					
People whose opinions I value encourage me to use Facebook					
People who are important to me support me to use Facebook					
I will use Facebook in the Future					
I plan to use Facebook often					

2. In a **NORMAL DAY**, how much **TOTAL TIME** do you spend on Facebook?

- ☐ Less than 20 minutes
- ☐ 20 to 40 minutes
- ☐ 40 minutes- 1hour
- ☐ 1 to 2 hours
- ☐ More than 2 hours

3. What is the **TOTAL number** of friends you currently have on Facebook?

- ☐ Less than 100
- ☐ 100 - 200

- ☐ 200 - 300
- ☐ 300 - 400
- ☐ More than 400

4. Please describe your feelings about the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Facebook is important to my university experience					
Facebook is a part of my everyday activity					
I am proud to tell people I am on Facebook					
I feel out of touch when I haven't logged onto Facebook for a while					
I feel I am a part of the Facebook community					
I would be sorry if Facebook shuts down					

5. To understand you more, please describe your feelings about the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I am good at predicting how someone will feel					
I am quick to spot when someone in a group is feeling awkward or uncomfortable					
Other people tell me I am good at understanding how they are feeling and what they are thinking					
I find it hard to know what to do in a social situation					
I often find it hard to judge if something is rude or polite					

6. Bring to mind a friend on Facebook that you trust, then describe your feelings about the following statements:

I believe that:	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
He/she would act in my best interest					
If I required help, he/she would do the best to help me					

He/she was interested in my well-being, not just his/her own					
I would characterize him/her as honest					
He/she was sincere and genuine					

I usually:	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
Like his/her posts					
Share posts with him/her					
Exchange private messages with him/her					
Visit his/her profile page to check for his/her news					

7. Please describe your feelings about the following statements (*about your relationship with that friend you have in mind***):**

	Strongly Disagree	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
I want my relationship with him/her to last for a very long time					
I am committed to maintaining my relationship with him/her					
I feel very attached to our relationship- very strongly linked to him/her					
I want our relationship to last forever					

Imagine this friend you have in mind **hacked** your Facebook account **once**. When you find out about it and you confront him/her, he/she **apologizes** to you and doesn't do it again.

8. How severe is this offense for you?

- ☐ not severe at all
- ☐ Somewhat severe
- ☐ Extremely severe

9. Please, describe your feelings about the following statements <u>AFTER hacking your account</u>.

	Strongly Disagree	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**

I wish that something bad would happen to him/her					
I want to see him/her hurt and miserable					
I'll make him/her pay					
I cut off the relationship with him/her					
I live as if he/she doesn't exist, isn't around					
I keep as much distance between us as possible					
I find it difficult to act warmly toward him/her					
I don't trust him/her					
I withdraw from him/her					
I avoid him/her					

10.

I believe that : (AFTER hacking your account)	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
He/she would act in my best interest					
If I require help, he/she would do its best to help me					
He/she was interested in my well-being, not just his/her own					
I would characterize him/her as honest					
He/she was sincere and genuine					

I Will: (AFTER hacking your account)	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
Like his/her posts					
Share posts with him/her					
Exchange private messages with him/her					
Visit his/her profile page to check for his/her news					

Finally, allow us to ask few questions about you.

11. What is your gender?

☐ Male

- ☐ Female

12. What is your age?

- ☐ under 18
- ☐ 18 - 24
- ☐ 25 - 30
- ☐ 31 - 40
- ☐ Older than 40

13. Are you?

- ☐ Married
- ☐ Divorced
- ☐ Widowed
- ☐ In a relationship
- ☐ Single

14. What is your highest degree or the current year of school?

- ☐ Freshman
- ☐ 2nd year
- ☐ 3rd year
- ☐ Master
- ☐ Doctorate

15. Which language do you use the most in your online communication?

- ☐ Arabic
- ☐ French
- ☐ English
- ☐ Spanish
- ☐ Others

Appendix D

Hypothetical offenses (2×2×2 scenarios)

Imagine this friend you have in mind **hacked** your Facebook account **once**. When you find out about it and you confront him/her, he/she **apologizes** to you and doesn't do it again.
Imagine this friend you have in mind **hacked** your Facebook account **once**. When you find out about it and you confront him/her, he/she does **not apologize** to you.
Imagine this friend you have in mind **hacked** your Facebook account **many times**. When you find out about it and you confront him/her, he/she **apologizes** to you.
Imagine this friend you have in mind **hacked** your Facebook account **many times**. When you find out about it and you confront him/her, he/she does **not apologize** to you.
Imagine this friend you have in mind shares **once** a photo of you on his Facebook wall **without asking you for permission**. When you find out about it and you confront him/her, he/she **apologizes** to you and **removed the photo**.
Imagine this friend you have in mind shares **once** a photo of you on his Facebook wall **without asking you for permission**. When you find out about it and you confront him/her, he/she does **not apologize** to you and **keeps** the photo on his Facebook.
Imagine this friend you have in mind shares a photo of you on his Facebook wall **without asking you for permission many times**. When you find out about it and you confront him/her, he/she **apologizes** to you and **removed the photos**.
Imagine this friend you have in mind shares a photo of you on his Facebook wall **without asking you for permission many times** . When you find out about it and you confront him/her, he/she does **not apologize** to you and **keeps** the photo on his Facebook.

Appendix E

Fuzzy Rules

1. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is High) and (Trust is High) then (Forgiveness is Low)
2. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is High) and (Trust is Low) then (Forgiveness is Very Low)
3. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is High) and (Trust is Medium) then (Forgiveness is Very Low)
4. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is Medium) and (Trust is High) then (Forgiveness is Low)
5. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is Medium) and (Trust is Medium) then (Forgiveness is Very Low)
6. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is Medium) and (Trust is Low) then (Forgiveness is Very Low)
7. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is Low) and (Trust is High) then (Forgiveness is Very Low)
8. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is Low) and (Trust is Medium) then (Forgiveness is Very Low)
9. If (Frequency is Many) and (Severity is Extremely Severe) and (Empathy is Low) and (Trust is Low) then (Forgiveness is Very Low)
10. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is High) and (Trust is High) then (Forgiveness is Medium)
11. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is High) and (Trust is Medium) then (Forgiveness is Medium)
12. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is High) and (Trust is Low) then (Forgiveness is Low)

13. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is Medium) and (Trust is High) then (Forgiveness is Medium)
14. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is Medium) and (Trust is Medium) then (Forgiveness is Low)
15. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is Medium) and (Trust is Low) then (Forgiveness is Low)
16. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is Low) and (Trust is High) then (Forgiveness is Medium)
17. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is Low) and (Trust is Medium) then (Forgiveness is Low)
18. If (Frequency is Many) and (Severity is Somehow Severe) and (Empathy is Low) and (Trust is Low) then (Forgiveness is Low)
19. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is High) and (Trust is High) then (Forgiveness is Very High)
20. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is High) and (Trust is Medium) then (Forgiveness is High)
21. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is High) and (Trust is Low) then (Forgiveness is Medium)
22. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is Medium) and (Trust is High) then (Forgiveness is High)
23. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is Medium) and (Trust is Medium) then (Forgiveness is Medium)
24. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is Medium) and (Trust is Low) then (Forgiveness is Medium)
25. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is Low) and (Trust is High) then (Forgiveness is High)
26. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is Low) and (Trust is Medium) then (Forgiveness is Medium)

27. If (Frequency is Many) and (Severity is Not Severe) and (Empathy is Low) and (Trust is Low) then (Forgiveness is Low)
28. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is High) and (Trust is High) then (Forgiveness is High)
29. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is High) and (Trust is Medium) then (Forgiveness is Medium)
30. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is High) and (Trust is Low) then (Forgiveness is Medium)
31. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is Medium) and (Trust is High) then (Forgiveness is High)
32. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is Medium) and (Trust is Medium) then (Forgiveness is Low)
33. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is Medium) and (Trust is Low) then (Forgiveness is Very Low)
34. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is Low) and (Trust is High) then (Forgiveness is Medium)
35. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is Low) and (Trust is Medium) then (Forgiveness is Low)
36. If (Frequency is Once) and (Severity is Extremely Severe) and (Empathy is Low) and (Trust is Low) then (Forgiveness is Low)
37. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is High) and (Trust is High) then (Forgiveness is Very High)
38. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is High) and (Trust is Medium) then (Forgiveness is Medium)
39. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is High) and (Trust is Low) then (Forgiveness is Medium)
40. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is Medium) and (Trust is High) then (Forgiveness is High)

41. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is Medium) and (Trust is Medium) then (Forgiveness is Medium)
42. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is Medium) and (Trust is Low) then (Forgiveness is Low)
43. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is Low) and (Trust is High) then (Forgiveness is Medium)
44. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is Low) and (Trust is Medium) then (Forgiveness is Low)
45. If (Frequency is Once) and (Severity is Somehow Severe) and (Empathy is Low) and (Trust is Low) then (Forgiveness is Low)
46. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is High) and (Trust is High) then (Forgiveness is Very High)
47. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is High) and (Trust is Medium) then (Forgiveness is Very High)
48. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is High) and (Trust is Low) then (Forgiveness is High)
49. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is Medium) and (Trust is High) then (Forgiveness is Very High)
50. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is Medium) and (Trust is Medium) then (Forgiveness is High)
51. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is Medium) and (Trust is Low) then (Forgiveness is Medium)
52. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is Low) and (Trust is High) then (Forgiveness is High)
53. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is Low) and (Trust is Medium) then (Forgiveness is Medium)
54. If (Frequency is Once) and (Severity is Not Severe) and (Empathy is Low) and (Trust is Low) then (Forgiveness is Low)

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