# Dynamically Learning Sources of Trust Information: Experience vs. Reputation

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## ABSTRACT

Trust is essential when an agent must rely on others to provide resources for accomplishing its goals. When deciding whether to trust, an agent may rely on, among other types of trust information, its past experience with the trustee or on reputations provided by third-party agents. However, each type of trust information has strengths and weaknesses: trust models based on past experience are more certain, yet require numerous transactions to build, while reputations provide a quick source of trust information, but may be inaccurate due to unreliable reputation providers. This research examines how the accuracy of experience- and reputation-based trust models is influenced by parameters such as: frequency of transactions with the trustee, trustworthiness of the trustee, and accuracy of provided reputations. More importantly, this research presents a technique for dynamically learning the best source of trust information given these parameters. The demonstrated learning technique achieves payoffs equal to those achieved by the best single trust information source (experience or reputation) in nearly every scenario examined.

## Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *Intelligent Agents, Multiagent Systems*

## General Terms

Algorithms, Experimentation.

## Keywords

Trust, Reputation, Learning, Multi-Agent Systems.

## 1. INTRODUCTION

Trust among individuals is essential for transactions. Often an individual does not have the resources—such as tangible goods, information, or services—to accomplish its goals alone. In these cases, the individual may obtain needed resources through transactions with others. In a transaction, two individuals make an (implicit or explicit) exchange agreement; however, the trusting agent is exposed to risk, since the trustee agent may fail to execute the transaction according to the exchange agreement. A trustee's failure to fulfill a transaction may be unintentional, for example, if the trustee miscalculates its ability to meet the terms of the exchange agreement. Alternatively, a trustee may intentionally sabotage the transaction, perhaps for a monetary benefit or to harm a truster who is also a competitor. A truster can reduce its risk by conducting transactions with those trustees most likely to fulfill agreements.

Trusters may use several techniques for building models of the trustworthiness of trustees, including transaction experiences, reputations, group association (credentials), appearances, or third-party transaction observation [4]. Many of these techniques are derived from human methods for assessing trustworthiness of other humans. In particular, this research will address the relationship between experience-based and reputation-based trust modeling. Experience-based trust modeling [1, 12] occurs when a truster uses the outcomes of its previous transactions with a trustee to estimate that trustee's future trustworthiness. Experience-based trust modeling is advantageous when agents have opportunities for numerous, repeated interactions. When the outcomes of interactions are observable, transaction experiences provide a truster with trustworthiness feedback that is certain. Unfortunately, basing trust on transaction experiences means risk exposure is unavoidable; trusters must first conduct transactions to evaluate a trustee's trustworthiness characteristics [4].

In reputation-based trust modeling [9, 17, 18], a truster builds its trust model of a potential trustee by requesting trust information, or reputations, from third-party agents, here called reputation providers. Adapted from [3], a reputation is a (not necessarily truthful) communication from one agent to another about the sender's trust in a third subject-agent. Reputation exchange is useful for quickly learning trustworthiness characteristics of potential trustees [18]. In systems with infrequent transactions (typical of large populations), since experience-based trust modeling is infeasible, reputation exchange is advantageous. Further, reputation exchange reduces a truster's risk exposure; a truster risks only the price (if any) of reputations it purchases, rather than the value of resources exchanged in a potential transaction. Agents entering a multi-agent system can quickly learn trust models by requesting reputations from more knowledgeable agents. However, reputation-based trust modeling requires that at least some agents in the system have conducted transactions with the agent whose trustworthiness is being modeled. Also, though a truster may assume its observations of transaction outcomes (the information used to build experience-based trust models) are certain, reputations (the information used


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to build reputation-based trust models) received from other agents introduce uncertainty, since reputation providers may be inaccurate or lying. Therefore, a truster has the additional task of assessing the accuracy of reputations it receives and the trustworthiness of the agents providing them. Lastly, if a truster chooses to include both reputations and experiences in its trust models, the agent must decide how to combine both types of trust information to produce a usable model for decision-making.

Trust assessment in multi-agent systems is essential for agents operating in numerous domains. In e-commerce environments (eBay, Amazon), agents acting on behalf of buyers must assess the trustworthiness of potential sellers to deliver purchased goods. Agents seeking recommendations via online referral networks like Epinions or Bizrate must verify the accuracy of received referrals. For agents operating in online social networks, such as MySpace, Friendster, or LinkedIn, trust assessment is necessary for identifying fake profiles, isolating online predators, and verifying the accuracy of information exchanged among "friends." The large range of these potential applications justifies the value of trust models based on both experience (for extended relationships) and reputations (for one-time transactions).

Researchers have developed successful algorithms for either experience- [10, 13] or reputation-based [14, 15] trust modeling, assuming system parameters are conducive to either only experience-based (numerous repeated transactions) or only reputation-based (one-time transactions) trust modeling. But several environments can be considered "hybrids"—experience- and reputation-based trust modeling techniques are both useful tools depending on changing system characteristics. For example, online social networks make use of both experiences and reputations when participants seek out new friends via reputations, then decide whether to keep friends based on interactions over time. Barber and Kim [5] have compared experience- vs. reputation-based trust modeling, only to confirm the intuitive notions that experience is effective over long term transaction histories, but reputations give an accurate picture more quickly, assuming reputation providers are accurate. However, their work fails to consider the accuracy of provided reputations and trustworthiness characteristics of trustees, important factors influencing the effectiveness of both experience- and reputation-based trust modeling.

This work identifies parameters affecting the best form of trust modeling for a given multi-agent system. A parameter $\psi$ is introduced, denoting the influence of experience versus reputations on an agent's trust decisions. Experimental results demonstrate the best $\psi$ value for given scenarios, varying transaction frequency, accuracy of provided reputations, and trustee trustworthiness. Finally, this presents a learning technique which adapts to a given set of system characteristics and identifies the best type of trust-modeling for the scenario. Experimental results demonstrate that learning $\psi$ performs as well as static $\psi$ selection in wide variety of scenarios.

# 2. REINFORCEMENT LEARNING FOR SELECTING TRUST MODELS

Since both the trustworthiness characteristics of potential trustees and reputation accuracy may change quickly; an agent must adapt its own trust decisions to continually achieve maximum payoff despite these system dynamics. Reinforcement learning has been successfully applied to strategies for deciding whom to trust in agent transactions [2, 6, 16]; however this approach also applies learning to the evaluation of the type of trust model—experience- or reputation-based—from which to derive these decisions.

Reinforcement learning is an advantageous technique for determining which type or combination of trust models to utilize in making trust decisions. The truster can learn, via rewards, the best trust model without knowing a priori the combination of system conditions favoring each type of trust model. The truster maintains an explicit goal ("maximize earnings") and judges success by observing the outcomes (transaction payoffs) of actions taken (which trust model type to use). In particular, Q-learning [11] requires no model of the agent's environment and can be used in real-time. This is valuable for learning the best trust model type, since modeling the relationships of factors affecting model selection—including reputation accuracy, trustworthiness of trustees, and transaction frequency—is extremely complex.

## 2.1 Learning Experience-Based Trust Models

Experience-based trust modeling is, by definition, a reinforcement learning problem. The truster first decides whether to trust or not trust. Not trusting yields a net payoff of zero to both the trustee and truster, since no fundamental transaction takes place. If the truster chooses to trust, it pays $P_r$ to the trustee. The trustee then chooses a resource valuated at $P_e$ to return to the truster. The trustee is considered trustworthy in the transaction if $P_e - P_r > 0$. If $P_e - P_r < 0$, the trustee is considered untrustworthy in the transaction.

The truster's Markov Decision Process for determining whether to trust a given trustee is shown in Figure 1. In this case, the process shows a single state ("Transaction Opportunity Initiated") with two possible action choices ("trust," $T$, and "not trust," $\neg T$). The "not trust" action has a single outcome: no transaction occurs, and no payoff is realized. The "trust" action has multiple outcomes (the two extreme outcomes are shown in the figure), depending on the payment $P_e$ determined by the trustee. Since the truster does not know the likelihoods of the trustee paying different values of $P_e$, the truster cannot easily determine the expected reward, $R$, of choosing the "trust" action. However, the agent can produce an estimate of the expected reward of choosing "trust," $Q(T)$, where $T$ represents the decision choice. $Q(T)$ can be compared against the zero reward for choosing "not trust" ($Q(\neg T) = 0$). If the value $Q(T)$ (for "trust") is positive, the truster should trust; if negative, then "not trust" should be selected.

Reputation-based trust modeling describes the process of collecting reputations from reputation providers to determine whether to trust a potential trustee in a transaction. It is assumed that the received reputations communicate values $Q^i(T)$ (where $i$ designates the reputation provider), evaluating the expected reward $P_e - P_r$ of trusting a given subject-agent (potential trustee). Even if a truster chooses to rely solely on reputations when making its decisions about whom to trust, it can use the transaction result as feedback to update its experience-based trust model ($Q(T)$ value). To take advantage of the benefits of both experience- and reputation-based modeling—that is, both the agent's own $Q(T)$ value and $Q^i(T)$ values received from reputation providers—an agent must know when to rely on which type of model and how to integrate conflicting values to make the trusting decision.

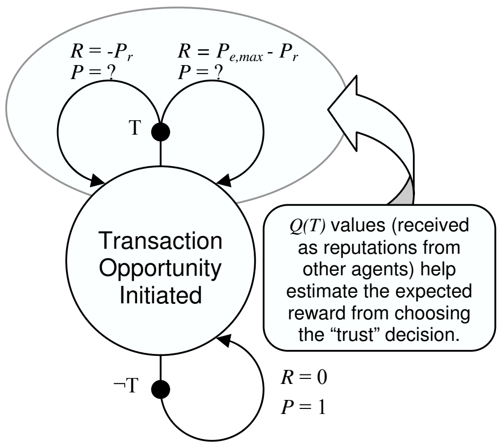


**Figure 1. Markov decision process for truster's decision—based on both experience and reputations—about trusting a trustee (assumes truster and trustee decisions are binary).**

## 2.2 Learning ψ

This research employs a parameter ψ to perform a weighting between reputation-based trust modeling and experience-based trust modeling. If ψ = 0, no weight is given to reputations, and the truster decides whether to trust only based on previous experience, according to reinforcement learning technique described in Section 2.1. Conversely, if ψ = 1, the experience-based model's $Q(T)$ value is given no weight; instead, the truster decides whether to trust based on an average of $Q^i(T)$ received as reputations. For a given ψ value, $Q'(T)$, the actual "trust" value used for comparison against the "not trust" value of zero, is calculated as:

$$Q'(T) = (1-\psi)Q(T) + \psi\left(\frac{\sum_{i\in I} Q^i(T)}{|I|}\right) \qquad \text{Equation 1}$$

where $I$ represents the set of reputation providers, in this timestep, about the given potential trustee. Note that all received reputations are equally represented (through averaging) in the reputation-based trust model; the selection of which reputations to request is not addressed in this work.

After deciding whether to trust a potential trustee, the truster observes with certainty the outcome of the transaction. If the truster chooses to "not trust" then the process of updating the $Q(\neg T)$ value is trivial; $Q(\neg T)$ remains zero, since no transaction takes place. If the truster chooses to "trust," then it uses its reward $P_e$ - $P_r$ to update its value for $Q(T)$.

Deciding the value of ψ—or the proportion of reliance on experience- vs. reputation-based trust models—is difficult because the accuracy of experience vs. reputations is dependent on several parameters. In general, experience-based trust modeling is favorable in small agent systems with frequent, repeated transactions among agents. In these systems, agents have many opportunities to transact with others and, thus, to learn experience-based trust models. Reputation-based trust modeling is more suited to large agent systems, in which transactions are sparse, since agents have few opportunities to interact and must obtain trust information vicariously through reputation exchange.

An appropriate value for ψ depends on many factors, including number of agents in the system, frequency of fundamental transactions among agents, frequency of reputation transactions among agents, truthfulness of communicated reputations, and trustworthiness in fundamental transactions. Not only is it difficult to determine which type of trust modeling—experience-based or reputation-based—is best for a given system, but it may be more difficult to predict what combination of both types of models will produce the highest-payoff decisions. For example, experiments by Fullam and Barber using the ART Testbed [8] show that experience-based trust models are favored when potential trustees are trustworthy (because the truster does not suffer loss when risking transactions to build its experience history), but reputation-based models are superior when the provided reputations are very accurate [7]. Further, an agent may not have enough knowledge about the agent system to make such a decision regarding the selection of ψ. Therefore, it is beneficial for an agent to dynamically learn ψ values, selecting the combination of experience- and reputation-based trust models depending on system characteristics, including accuracy of provided reputations, trustworthiness of potential trustees, and frequency of transactions.

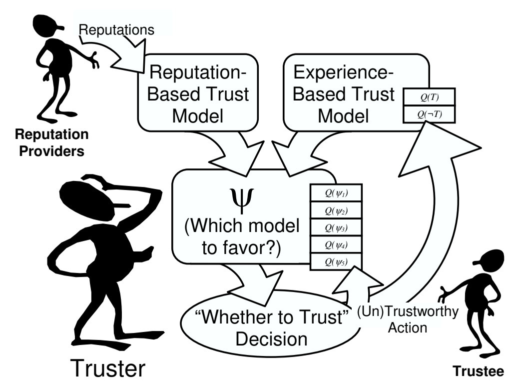


**Figure 2. The ψ-learning process for a truster agent. Provided reputations influence reputation-based trust model accuracy, while trustee action trustworthiness impacts experience-based trust model. Accuracy of both reputation- and experience-based trust models impacts the ψ value learned.**

Figure 2 demonstrates the process by which a truster builds its reputation- and experience-based trust models and learns the best ψ value for given system characteristics. To learn ψ, the truster agent maintains a secondary table with an entry for each ψ option (the number of options, between zero and one inclusive, depends on the level of precision desired by the agent designer). Each value $Q(\psi)$ represents the estimated average per-transaction payoff associated with using the given ψ value to determine $Q'(T)$

for each transaction in a given timestep. The $\psi$ learning process occurs as follows. A $\psi$ value, selected for the current timestep, is used to calculate $Q'(T)$ for each transaction opportunity in the timestep. A decision is made whether to trust for each transaction opportunity based on these values (a positive $Q'(T)$ value signifies a preference for trusting, while a negative $Q'(T)$ value signifies a preference for not trusting). Concurrently, separate decisions about whether to trust in each transaction opportunity are calculated, though not applied, using each possible $\psi$ value. The results of each transaction are observed (including hypothetical transactions for which the truster has chosen to not trust), and the average per-transaction payoff for this timestep associated with each possible $\psi$ value is calculated as an average of payoffs over all transactions. A transaction's payoff equals zero if it does not take place due to a "not trust" decision. If a "trust" decision is recommended, then the payoff is calculated as $P_e$ - $P_r$. The calculated payoff for each $\psi$ value is used to update respective $Q(\psi)$ values in the table. In the next timestep, a new $\psi$ is selected, favoring the highest $Q(\psi)$ value in the table.

# 3. EXPERIMENTS

These experiments assess which type of trust-modeling technique—experience ($\psi$ = 0.0), reputation ($\psi$ = 1.0), or a combination—yields the most successful transactions for a truster agent in scenarios in which reputation accuracy and trustee trustworthiness characteristics are varied. Further, the experiments demonstrate that learning $\psi$ produces transactions as successful as the best static $\psi$ value across a wide variation in scenarios.

## 3.1 Experiment Setup

Experiment parameters are listed in Table 1. Each experiment measures the total earnings over time of a single truster agent in a system with $n$ = 1000 trustee agents. In each timestep, the truster is presented with opportunities to transact with $m$ = 100 randomly-selected trustees. The truster's goal is to maximize its earnings by correctly determining, for each transaction opportunity, whether to trust the potential trustee. To make these determinations, the truster must choose whether to rely on past transactions (experience), reputations, or both.

If the truster chooses to trust, it makes a payment $P_r$ of 10 units to the trustee (if the truster chooses to not trust, no payment is made). The trustworthiness of a trustee's transaction response is determined by its return payment $P_e$ to the truster, taken from the distribution $N(\mu_T, \sigma_T)$ ($\sigma_T$ equals 10 and $\mu_T$ takes on values in the set {5, 8, 10, 12, 15}). The trustee's response distribution mean determines the trustee's average trustworthiness, while the distribution standard deviation determines the variation in the trustee's behavior ($P_e > P_r$ is feasible, since the truster's and trustee's valuations of both payments may differ; the trustee's valuation of its payment to the truster may be less than its valuation of the payment it receives). For clarity in evaluating experimental results, all trustees behave according to the same return payment distribution; however, this similarity of behavior is unknown to the truster, who maintains independent trust models for each potential trustee.

Since the problem of selecting the most accurate reputation providers is beyond the scope of this paper, the truster's request for reputations is answered by a single reputation provided by the simulation, imitating an aggregate of reputation values from multiple reputation providers. The reputation value is produced from a distribution $N(\mu_T, \sigma_R)$, where $\sigma_R$ describes reputation accuracy (smaller $\sigma_R$ values signify more accurate reputations) and takes on a value of either 0.1 or 10.0.

**Table 1. Experiment Parameters.**

| | |
|---|---|
| Timesteps per Run | 10000 |
| Potential Trustees ($n$) | 1000 |
| Transactions per Timestep ($m$) | 100 |
| Truster Payment ($P_r$) | 10 |
| Average Trustee Payment ($\mu_T$) | {5, 8, 10, 12, 15} |
| Trustee Payment Standard Deviation ($\sigma_T$) | 10 |
| Reputation Error Standard Deviation ($\sigma_R$) | {0.1, 10.0} |
| Reputation- vs. Experience-Based Trust Model Influence ($\psi$) | {0.0, 0.5, 1.0, learned} |

The truster's $\psi$ value is varied for different scenarios. When $\psi$ = 0.0, the truster relies solely on experience (past transactions) to determine whom to trust. When $\psi$ = 1.0, the truster replies solely on reputations, and when $\psi$ = 0.5, both experience- and reputation-based models are considered, according to Equation 1. Each of these three static $\psi$ values are compared against the $\psi$-learning technique described in Section 2.2, in which the $\psi$ value is dynamically learned according to system parameters. The truster employs the following learning parameters (for the truster's experience-based model, as well as $\psi$ value, if being learned): learning rate ($\alpha$) of 0.5, discount factor ($\gamma$) of 0.0, and temperature, or degree of exploration ($\tau$), of 0.01. A scenario is run three times for each combination of parameters (for 10,000 timesteps). Reputation accuracy $\sigma_R$, as well as trustee trustworthiness parameters $\mu_T$ and $\sigma_T$, are static over a single run. Cumulative earnings (payments received from trustees minus payments of 10 units made to trustees) are measured, and the results from the three runs are averaged.

## 3.2 Experiment Results

Experiment results in Figures 3-10 show truster earnings according to $\mu_T$ (trustee trustworthiness), $\sigma_R$ (reputation accuracy), and $\psi$ (trust modeling technique: experience-based, reputation-based, combination, or learned). Note that while experiments for $\mu_T$ = 10 are conducted, the results are not displayed here, because each trust-modeling technique, for both levels of reputation accuracy, yields average earnings of zero, since average trustee payments ($\mu_T$) equal truster payments ($P_r$).

When $\mu_T$ = 5, trustees are untrustworthy, trustees rarely provide any positive per-transaction earnings, and the truster loses 5 units of earnings per transaction, on average; therefore, the truster's net earnings are negative. For the case in which $\sigma_R$ = 0.1 (reputations are very accurate), as shown in Figure 3, the truster achieves minimal losses by relying on reputations. However, experience-based decisions achieve similar earnings after an initial model-learning period. The learning period presents a large risk to the truster when learning an experience-based model because per-transaction losses are high. However, when $\sigma_R$ = 10.0 (reputations are inaccurate), as shown in Figure 4, the truster achieves highest earnings (smallest losses) by always relying on experience, since the experience-based model improves with more transactions but reputations remain inaccurate. In both variations of reputation accuracy, both the ψ = 0.5 and ψ-learning techniques achieve nearly the same earnings as each of the best static-ψ values, even though the learned ψ values are very different (1.0 for $\sigma_R$ = 0.1 and 0.0 for $\sigma_R$ = 10.0).

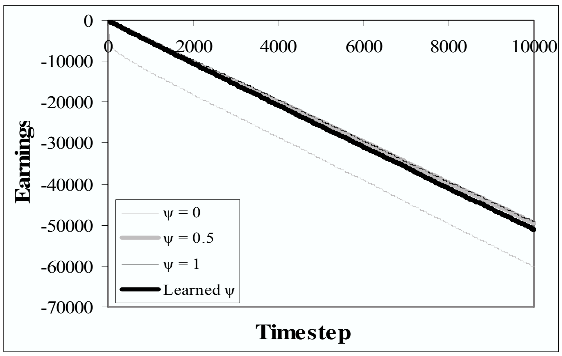


**Figure 3. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(5, 10)$ and reputation error standard deviation $\sigma_R = 0.1$.**

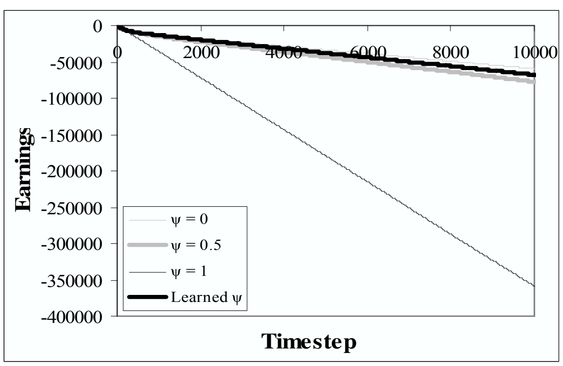


**Figure 4. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(5, 10)$ and reputation error standard deviation $\sigma_R = 10.0$.**

When $\mu_T$ = 8, trustees are usually untrustworthy, trustees occasionally provide positive per-transaction earnings and the truster loses 2 units of earnings per transaction, on average. For the case in which $\sigma_R$ = 0.1 (Figure 5), smallest losses are initially achieved by relying on reputations. However, as the experience-based model is built, its losses become smaller than those of the reputation-based model, most likely because the wide variation ($\sigma_T$) means that sometimes trustees actually yield a positive payoff (the ψ = 0.5 case behaves similarly to the ψ = 0.0 case). The experience-based model is more likely to explore and find opportunities for positive transactions, but reputations, close to $\mu_T$, always suggest "not trust." The number of timesteps before ψ = 0.0 earnings surpass ψ = 1.0 earnings depends how quickly experience-based models are built (how frequently the truster has the opportunity to transact with each trustee). In this scenario, though the ψ-learning technique learns to rely on reputations initially, it does not adapt to the experience-based models, and so fails to achieve earnings as high as those the experience-based model is eventually able to achieve. However, it is hypothesized that further adjustments of learning parameters will yield a ψ-learning technique more sensitive to changes in experience-model accuracy.

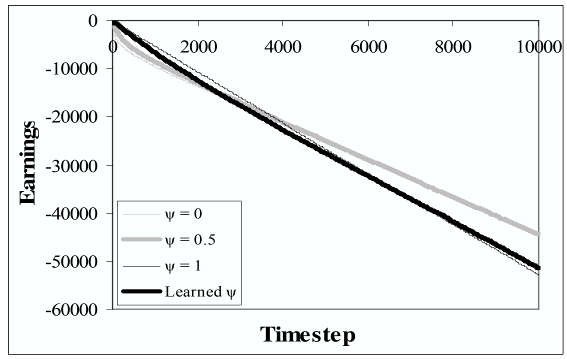


**Figure 5. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(8, 10)$ and reputation error standard deviation $\sigma_R = 0.1$.**

Figure 5 illustrates the importance of reputations during the "bootstrapping" period of building an experience-based trust model. Initially, since $\sigma_R$ = 0.1, reputations, rather than experiences, are the more accurate source of trust information. However, as the experience-based model is built over the course of numerous transactions, it becomes more accurate then the reputation-based model. In Figure 6 ($\mu_T$ = 8, $\sigma_R$ = 10.0), the bootstrapping period (in which reputations are more accurate than the experience-based model) is nearly non-existent; since $\sigma_R$ = 10.0, reputations are never more accurate than even the most primitive experience-based model.

Observing the bootstrapping period is key to understanding the relationship between the truster's experience- and reputation-based trust models and predicting when the truster's reliance should change from one to the other. Reputations, in proportion to their accuracy, are important for trust decisions as long as the experience-based trust model is still being built. Experiments not charted here confirm the intuitive notion that the number of timesteps needed for an experience-based trust model to converge—assuming trustee trustworthiness characteristics are static—is proportional to per-trustee transaction frequency (the number of potential trustees in the system divided by the number of total transaction opportunities per timestep). Further, the convergence period is extended when trustee trustworthiness characteristics are dynamic; the experience-based trust model must continually learn the trustees' new behavior. In fact, experience-based trust models may never converge if transactions are not frequent enough to keep pace with changes in trustee trustworthiness characteristics. During this bootstrapping period (before the experience-based trust model has converged), reputations are more reliable than the experience-based model, depending on reputation accuracy. Both time needed to bootstrap and failure to converge explain why reputations are essential to domains such as online marketplaces; in these environments, transactions are too infrequent to keep pace with trustee trustworthiness changes, rendering experience-based trust models ineffective compared to reputations.

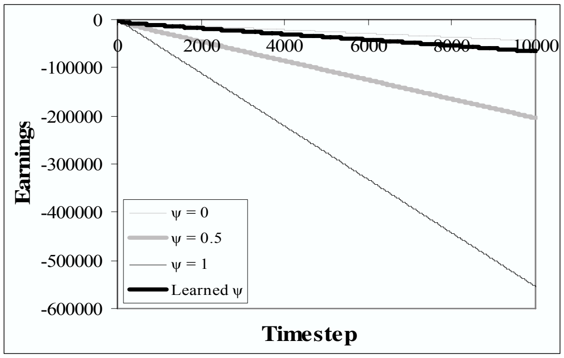


**Figure 6. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(8, 10)$ and reputation error standard deviation $\sigma_R = 10.0$.**

When $\mu_T$ = 8 and $\sigma_R$ = 10.0 (Figure 6), the truster achieves smallest losses by always relying on experience, though the losses are not as large as when $\mu_T = 5$, because trustees at $\mu_T = 8$ provide slightly higher payoffs. Reputation-based trust modeling suffers significantly bigger losses that the experience-based trust model, and the ψ = 0.5 case yields losses greater than ψ = 0.0, yet less than ψ = 1.0. For $\mu_T = 8$ and $\sigma_R = 10.0$, the ψ-learning technique achieves nearly the same earnings as the best static ψ value (ψ = 0.0).

When $\mu_T$ = 12, trustees are usually trustworthy, occasionally causing negative per-transaction earnings, though the truster gains 2 units of earnings per transaction, on average. For the case in which $\sigma_R = 0.1$ (Figure 7), reputation-based trust modeling yields the highest earnings, since reputations are very accurate, with ψ = 0.5 yielding slightly lower earnings. The ψ-learning technique achieves earnings near that of ψ = 0.0. Interestingly, for the case in which $\sigma_R$ = 10.0 (Figure 8), ψ = 0.5 achieves the highest earnings (slightly higher than ψ = 1.0), most likely because averaging input from both experience and reputations (though reputation accuracy is poor in this case), yields greater accuracy in decisions about whether to trust. The ψ-learning technique achieves earnings near that of ψ = 0.5 and significantly greater than both ψ = 1.0 and ψ = 0.0. In general, earnings due to all reputation-utilizing ψ values (0.5, 1.0, and ψ-learning) are lower for the $\sigma_R$ = 10.0 case than for the $\sigma_R$ = 0.1 case because reputations are less accurate for $\sigma_R = 10.0$.

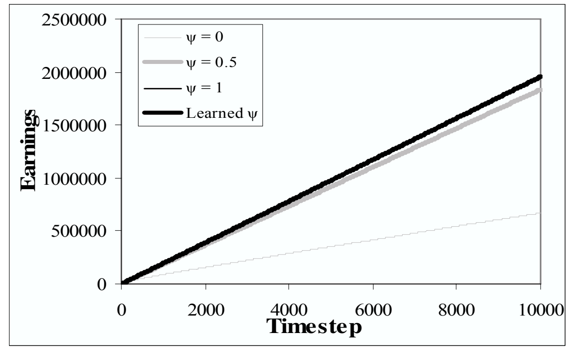


**Figure 7. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(12, 10)$ and reputation error standard deviation $\sigma_R = 0.1$.**

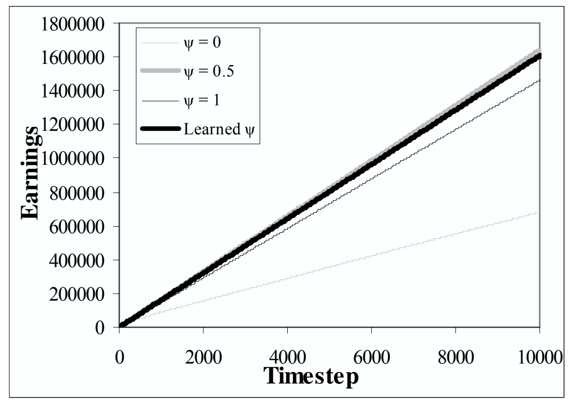


**Figure 8. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(12, 10)$ and reputation error standard deviation $\sigma_R = 10.0$.**

When $\mu_T$ = 15, trustees are trustworthy, rarely causing negative per-transaction earnings, and the truster gains 5 units of earnings per transaction, on average. For both cases of reputation accuracy, in which $\sigma_R = 0.1$ (Figure 9) and $\sigma_R = 10.0$ (Figure 10), all ψ values achieve high earnings, because trustees consistently yield high per-transaction earnings (therefore experience and reputations, both encouraging decisions to trust, are nearly always correct). The single exception is the ψ = 1.0 case when $\sigma_R = 10.0$; occasionally inaccurate reputations may suggest a decision to not trust, decreasing total earnings over time. It should be noted that the ψ-learning technique achieves earnings nearly as high as the highest static-ψ value for both the $\sigma_R = 0.1$ and $\sigma_R = 10.0$ cases.

Figures 11 and 12 show ψ values learned by the ψ-learning algorithm (100-point moving averages are displayed). Figure 11 compares learned ψ values for different trustee trustworthiness ($\mu_T$) when reputations have a low error standard deviation ($\sigma_R$ = 0.1). When trustees are untrustworthy ($\mu_T = 5$, $\mu_T = 8$), ψ values are near 1.0 during early timesteps; the learning-ψ truster relies on reputation-based trust modeling since reputations are very accurate and transactions result in significant loss. However, ψ values decrease over time (as experience-based trust models become more accurate), settling on ψ values that promote usage of both experience- and reputation-based trust modeling. When trustees are trustworthy ($\mu_T$ = 12, $\mu_T$ = 15), ψ values remain consistent over all timesteps. When $\mu_T$ = 12, ψ values remain consistently high; the learning-ψ truster relies on reputation-based trust modeling since reputations are very accurate and trustees are difficult to model based on experience (transactions do not consistently yield positive payoffs for trusters). When $\mu_T$ = 15, ψ values remain consistently near 0.6, showing that the learning-ψ truster relies on both experience and reputations.

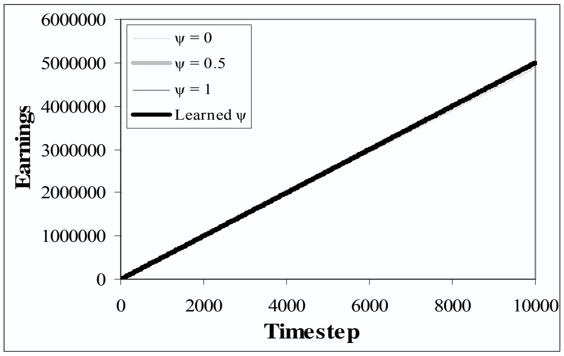


**Figure 9. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(15, 10)$ and reputation error standard deviation $\sigma_R = 0.1$.**

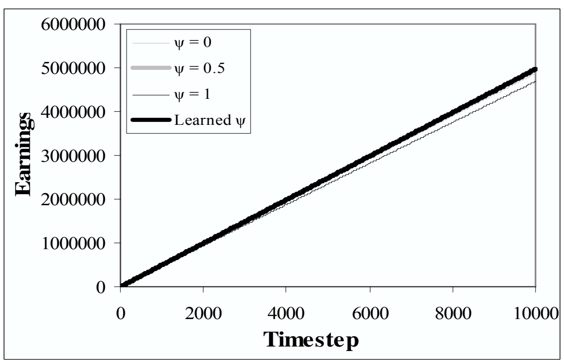


**Figure 10. Truster's transaction earnings for trustee trustworthiness characteristics $N(\mu_T, \sigma_T) = N(15, 10)$ and reputation error standard deviation $\sigma_R = 10.0$.**

Figure 12 compares learned ψ values for different trustee trustworthiness ($\mu_T$) when reputations have a high error standard deviation ($\sigma_R$ = 10.0). For all degrees of trustee trustworthiness, learned ψ values converge to values lower than those learned when reputations are more accurate ($\sigma_R$ = 0.1); when $\sigma_R$ = 10.0, the learning-ψ truster relies more on experience-based trust modeling since reputations are less accurate than the experience-based model the truster eventually builds. When trustees are untrustworthy ($\mu_T$ = 5, $\mu_T$ = 8), the learned ψ value takes longer to reach the converged, low value, because the risk of transacting with the untrustworthy trustee outweighs the inaccuracy of reputations, until sufficiently accurate experience-based models are built. When trustees are trustworthy ($\mu_T$ = 12, $\mu_T$ = 15), ψ values converge more quickly, and, in both cases, favor experience- over reputation-based trust modeling.

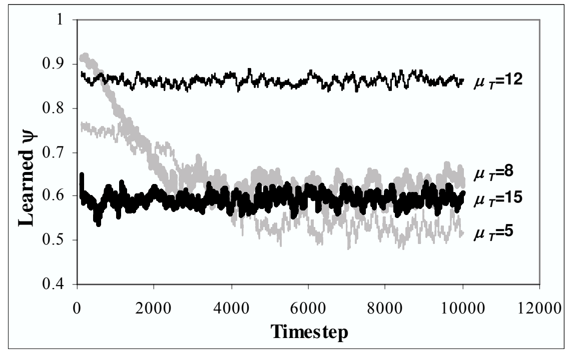


**Figure 11. Learned ψ values for trustee trustworthiness characteristics $N(\mu_T, 10)$ and reputation error standard deviation $\sigma_R = 0.1$.**

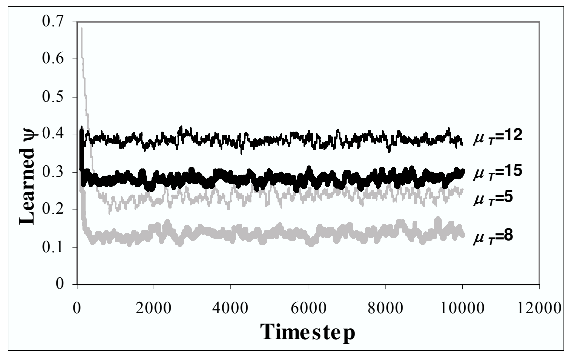


**Figure 12. Learned ψ values for trustee trustworthiness characteristics $N(\mu_T, 10)$ and reputation error standard deviation $\sigma_R = 10.0$.**

In summary, reputation-based models yield higher earnings over experience-based models when trustees are untrustworthy and reputations are accurate, though over time, experience-based models may become accurate enough to surpass the decision accuracy of reputation-based models. Experience-based models yield highest earnings when trustees are untrustworthy and reputations are inaccurate, because experience-based models become more accurate over time while reputation accuracy remains constant. When trustees are trustworthy, reputation-based models achieve more accurate decisions about whom to trust. When trustees yield occasionally negative, yet on average positive, per-transaction earnings, experience-based models do not achieve earnings as high as reputation-based models. However, when trustees are consistently trustworthy, experience-based models yield earnings as high as reputation-based models. Most importantly, learning ψ achieves earnings nearly as high as the best static ψ value in all scenarios except those in which trustees are usually untrustworthy, but occasionally provide positive per-transaction earnings; in this case, reputation-based models provide highest earnings early on, yet experience-based models later become more accurate.

# 4. CONCLUSIONS

This research identifies the best type of trust model—experience-based, reputation-based, or combination—for determining whom to trust over various systems with different transaction frequency, trustee trustworthiness, and reputation accuracy. The parameter $\psi$, determining the influence of experience versus reputations on trust decisions, is introduced. More importantly, this research demonstrates that a technique for dynamically learning $\psi$ identifies the best $\psi$ (combination of experience- and reputation-based models) over a wide range of system characteristics.

Several areas of future work will contribute to more robust decision-making about whom to trust. In some scenarios, the most appropriate $\psi$ value changes over time, for example, as experience-based models become more accurate with more transactions, or as reputation accuracy or trustee trustworthiness characteristics change. Further examination of learning parameters will improve the $\psi$-learning technique's ability to adapt to these best-$\psi$ changes. In addition, a truster should learn separate $\psi$ values for each potential trustee, since transaction frequency, accuracy of reputations, and trustee trustworthiness characteristics may vary from trustee to trustee. Also, reputation cost should be considered; high reputation costs may make reputation-based trust modeling infeasible, even when reputations are very accurate and experience-based trust models are not robust. Most importantly, this research assumes consistent reputation error and ignores the problem of identifying best reputation providers. Further research will examine cases in which reputation error varies due to improved reputations over time (as reputation providers build more accurate models) and variations in selected reputation providers from timestep to timestep.

# 5. ACKNOWLEDGMENT

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