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PAYMENT REMINDER TECHNIQUE WITH ENHANCED EFFICIENCY

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TITLE: “PAYMENT REMINDER TECHNIQUE WITH ENHANCED EFFICIENCY”

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TECHNICAL FIELD

This disclosure relates generally to the field of financial technology. More particularly, the disclosure focuses on enhancing efficiency of payment reminder techniques using machine learning.

BACKGROUND

In current process, payment reminders are generally sent by financial institutions to their customers as per a pre-defined schedule like after the bill is generated, before a certain number of days from the payment due date etc. A payment reminder may be a letter, an email, a phone call, a document or an SMS which may help the customers to pay their dues. Payment reminder systems help the company to maintain the track record of outstanding payments and results in timely payments of dues. Customers may also need a smooth and timely payment reminder system to receive advance warnings of payments due.

However, the schedule for such payment reminders in the currently available payment reminder system is not customized based on the customer's preferred time. For example, a customer may probably like to get reminded about the upcoming due bill payment on weekends, or in the weekday's morning and afternoon between a certain time window when he/she commutes by public transport, or in the evening of weekdays, or last/first day of the month when salary is paid to the customer by his/her employer. The date/time preference to receive the reminders may vary from customer to customer and if the reminder schedule can be customized based on their preferred time, the chances of making the bill payment seeing these reminders would be higher, and would help to avoid missed payment, late fees and customer dissatisfactions.

SUMMARY

According to some non-limiting embodiments, the present invention discloses system and methods to improve the efficiency of the payment reminder process. The system allows customers to get payment reminders at their preferred time of the day, preferred day of the week and preferred communication channel for example email, SMS or phone call. Customisation of payment reminder schedule as per the customer's preferred time and channel may result in the timely due payment. Customer may avoid missed payment and late fees with the help of the payment reminders. Hence the disclosed embodiments ensure the customer's comfort and satisfaction.

According to some aspects of the embodiment, a reinforcement learning technique may be used to derive the decisions based on parameters like customer's payment history, past reminder interactions at different timings, reminder channels (like email, SMS, phone call), and find the best possible timing and channel of communication for the customer to send the reminders of upcoming due bill payments. There are many available reinforcement learning algorithms, and for this solution, Q-learning is used.

BRIEF DESCRIPTION OF THE DRAWINGS AND APPENDICES

Additional advantages and details of non-limiting embodiments are explained in greater detail below with reference to the exemplary embodiments that are illustrated in the accompanying schematic figures, in which:

FIG. 1 illustrates an exemplary representation of payment reminder system.

FIG. 2 illustrates a flowchart that illustrates the step-by-step approach of payment reminder process.

DESCRIPTION OF THE DISCLOSURE

In the present document, the word "exemplary" is used herein to mean "serving as an example, instance, or illustration." Any embodiment or implementation of the present subject matter described herein as "exemplary" is not necessarily to be construed as preferred or advantageous over other embodiments.

While the disclosure is susceptible to various modifications and alternative forms, specific embodiments thereof have been shown by way of example in the drawings and will be described in detail below. It should be understood, however, that it is not intended to limit the disclosure to the particular forms disclosed, but on the contrary, the disclosure is to cover all modifications, equivalents, and alternative falling within the spirit and the scope of the disclosure.

The terms "comprises", "comprising", or any other variations thereof, are intended to cover a non-exclusive inclusion, such that a setup, device or method that comprises a list of components or steps does not include only those components or steps but may include other components or steps not expressly listed or inherent to such setup or device or method. In other words, one or more elements in a device or system or apparatus proceeded by “comprises… a” does not, without more constraints, preclude the existence of other elements or additional elements in the device or system or apparatus.

The terms "an embodiment", "embodiment", "embodiments", "the embodiment", "the embodiments", "one or more embodiments", "some embodiments", and "one embodiment" mean "one or more (but not all) embodiments of the invention(s)" unless expressly specified otherwise. The terms "including", "comprising", “having” and variations thereof mean "including but not limited to", unless expressly specified otherwise.

These and other features and characteristics of the present invention, as well as the methods of operation and functions of the related elements of structures and the combination of parts and economies of manufacture, will become more apparent upon consideration of the following description and the appended claims with reference to the accompanying drawings, all of which form a part of this specification, wherein like reference numerals designate corresponding parts in the various figures. It is to be expressly understood, however, that the drawings are for the purpose of illustration and description only and are not intended as a definition of the limits of the invention. As used in the specification and the claims, the singular form of “a,” “an,” and “the” include plural referents unless the context clearly dictates otherwise.

It will be apparent that systems and/or methods, described herein, can be implemented in different forms of hardware, software, or a combination of hardware and software. The actual specialized control hardware or software code used to implement these systems and/or methods is not limiting the implementations. Thus, the operation and behaviour of the systems and/or methods are described herein without reference to specific software code, it is understood that software and/or hardware can be designed to implement the systems and/or methods based on the description herein.

The present invention discloses systems and methods to enhance the efficiency of payment reminder process. The solution disclosed here proposes a payment reminder process that may send the reminders to the user at their preferred timing for example the reminder may be sent to the customer at a particular time of the day, on particular days in the week and on specific communication channels which they may prefer.

Machine learning techniques may help to send the payment reminder alerts at user’s preferred time and communication channel efficiently. However, training a machine learning model accurately will require a large amount of training data. A reinforcement learning technique may be used to derive the decisions based on parameters like customer’s payment history, past reminder interactions at different timings, and reminder channels (like email, SMS, and phone call) and find the best possible timing and channel of communication for the customer to send the reminders of upcoming due bill payments.

Reinforcement Learning is a reward-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions. For each good action, the agent gets reward, and for each bad action, the agent gets a penalty. There are many available reinforcement learning algorithms. For this solution, Q-learning may be used.

Q-learning: Q-learning is a popular algorithm in the field of reinforcement learning. It is used to solve Markov Decision Processes (MDPs), where an agent learns to take actions in an environment to maximize its cumulative rewards over time. The agent maintains a Q-table that represents the expected rewards for each state-action pair, and through exploration and exploitation, it learns the best actions to take in different states. It is an off-policy reinforcement learning algorithm because the function learns from actions that are outside the current policy, like taking random actions, and therefore a policy is not needed.

The main idea behind the Q-Learning algorithm is the Bellman equation. Balman equation takes states(s) and action(a) as input. The equation simplifies the state values and state-action value calculation.:

$$Q^{new}(s_t,a_t) \leftarrow \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\Bigg(\underbrace{\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1},a)}_{\text{estimate of optimal future value}}}_{\text{new value (temporal difference target)}} - \underbrace{Q(s_t,a_t)}_{\text{old value}}\Bigg)}^{\text{temporal difference}}$$

where r_t is the reward received when moving from the state s_t to the state s_{t+1}, and α is the learning rate $(0 < \alpha \leq 1)$.

Note that $Q^{new}(s_t,a_t)$ is the sum of three factors:

- $(1-\alpha)Q(s_t,a_t)$: the current value weighted by the learning rate. Values of the learning rate near to 1 make the changes in Q more rapid.
- $\alpha\, r_t$: the reward $r_t = r(s_t,a_t)$ to obtain if action a_t is taken when in state s_t (weighted by learning rate)
- $\alpha\gamma \max_a Q(s_{t+1},a)$: the maximum reward that can be obtained from state s_{t+1} (weighted by learning rate and discount factor)

FIG. 1 illustrates an exemplary representation of payment reminder system 100 where customer's information such as customer's payment history, past reminder interactions, customer's outstanding balances and time elapsed since the last reminder is stored in the database 106. Also, the possible set of actions may be stored in the database (or disk) 106. The system may have a input/ output interface 102 through which customer's information may be provided. Further, the system 100 may have a processor 104 which may comprise the storage device to store the state and possible actions. Further, the database (or disk) 108 may store a trained model and Q-values based on state and action pair.

Figure 2 depicts a flowchart showing a method for the payment reminder system using Q-learning. The method starts at step 202, where a representation of system's state may be defined. The state may comprise the customer side payment information. For example, state may include customer's as customer's payment history, past reminder interactions, outstanding balances, and time elapsed since the last reminder.

At step 204, the set of possible actions may be defined. The action is the step taken by the agent when it is in a particular state. In the present scenario, action may correspond to the decisions on payment reminder timing and channel of communication, choosing the timing of the reminders and different channels for communication (email, SMS, phone call).

At step 206, a reward function is defined to provide the reward to the Q-learning agent. A reward is positive feedback which may be given when payment is received from the customer after reminder, and negative rewards may be given for late or missed payments. There may be penalties on sending too many reminders.

At step 208, a Q-table may be initialized to store the expected rewards for each state-action pair. A Q table helps to find the best action for each state in the environment. The Bellman Equation is used at each state to get the expected future state and reward and save it in a table to compare with other states. Initially, the values in the Q-table may be random. Further the table is updated.

At step 210, the Q-learning algorithm may be trained to learn the optimal policy (strategy) for sending payment reminders. The agent interacts with the customers, observing its state, selecting actions based on the Q-table (using exploration strategies like epsilon-greedy), and receiving rewards. The Q-table is updated using the Bellman equation to revise the action selection policy through multiple iterations and learning episodes.

At final step 212, the model may be deployed to the payment reminder system 100. It may make decisions on when and how to send the reminders to customers based on what it has learned during training and adapt its behavior based on the accumulated experiences and Q-value updates.

Hence, using the technique of reinforcement learning and more particularly Q -learning may optimize the payment reminder system. This technique with improved efficiency and accuracy of payment reminder process may help the customers avoid late or missed payments and enhance customer satisfaction.

In an embodiment, one or more computer-readable storage media may be utilized in implementing embodiments consistent with the present disclosure. A computer-readable storage medium refers to any type of physical memory on which information or data readable by a processor may be stored. Thus, a computer-readable storage medium may store instructions for execution by one or more processors, including instructions for causing the processor(s) to perform steps or stages consistent with the embodiments described herein. A non-transitory computer readable medium may include media such as magnetic storage medium, optical storage, volatile and non-volatile memory devices etc. Further, non-transitory computer-readable media may include all computer-readable media except for a transitory. The code implementing the described operations may further be implemented in hardware logic (e.g., an integrated circuit chip, Programmable Gate Array (PGA), Application Specific Integrated Circuit (ASIC), etc.).

The described operations may be implemented as a method, system or article of manufacture using standard programming and/or engineering techniques to produce software, firmware, hardware, or any combination thereof. The described operations may be implemented as code maintained in a “non-transitory computer readable medium”, where a processor may read and execute the code from the computer readable medium. The processor is at least one of a microprocessor and a processor capable of processing and executing the queries.

The illustrated steps are set out to explain the exemplary embodiments shown, and it should be anticipated that ongoing technological development will change the manner in which particular functions are performed. These examples are presented herein for purposes of illustration, and not limitation. Further, the boundaries of the functional building steps have been arbitrarily defined herein for the convenience of the description. Alternative boundaries can be defined so long as the specified functions and relationships thereof are appropriately performed. Alternatives (including equivalents, extensions, variations, deviations, etc., of those described herein) will be apparent to persons skilled in the relevant art(s) based on the teachings contained herein. Such alternatives fall within the scope and spirit of the disclosed embodiments. Also, the words "comprising," "having," "containing," and "including," and other similar forms are intended to be equivalent in meaning and be open ended in that an item or items following any one of these words is not meant to be an exhaustive listing of such item or items or meant to be limited to only the listed item or items. It must also be noted that as used herein, the singular forms “a,” “an,” and “the” include plural references unless the context clearly dictates otherwise.

All patents, patent applications, publications, and descriptions mentioned above are herein incorporated by reference in their entirety for all purposes. None is admitted to being prior art.

Although the invention has been described in detail for the purpose of illustration based on what is currently considered to be the most practical and preferred embodiments, it is to be understood that such detail is solely for that purpose and that the invention is not limited to the disclosed embodiments, but, on the contrary, is intended to cover modifications and equivalent arrangements that are within the spirit and scope of the invention. For example, it is to be understood that the present invention contemplates that, to the extent possible, one or more features of any embodiment can be combined with one or more features of any other embodiment.

PAYMENT REMINDER TECHNIQUE WITH ENHANCED EFFICIENCY

ABTRACT

The present disclosure relates to the payment reminder process. It proposes to improve the efficiency of payment reminder process by sending the reminders at customer's preferred timing (like at what time in the day, on which day of the week, on which date of the month) and communication channel (like email, sms, phone call). A reinforcement learning technique and particularly Q-learning may be used to derive the decisions based on parameters like customer's payment history, past reminder interactions at different timings, reminder channels (like email, sms, phone call); and find the best possible timing and channel of communication for the customer to send the reminders of upcoming due bill payments.

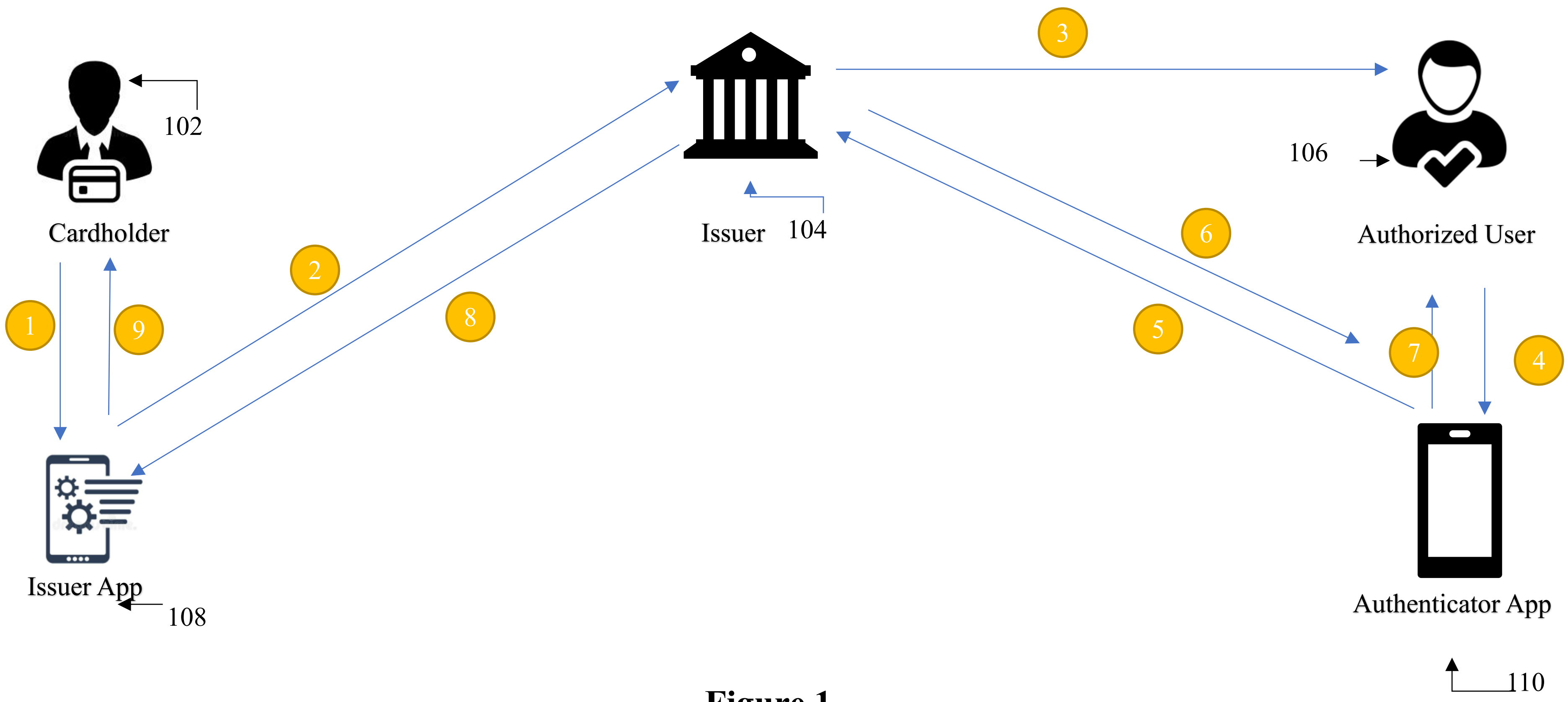
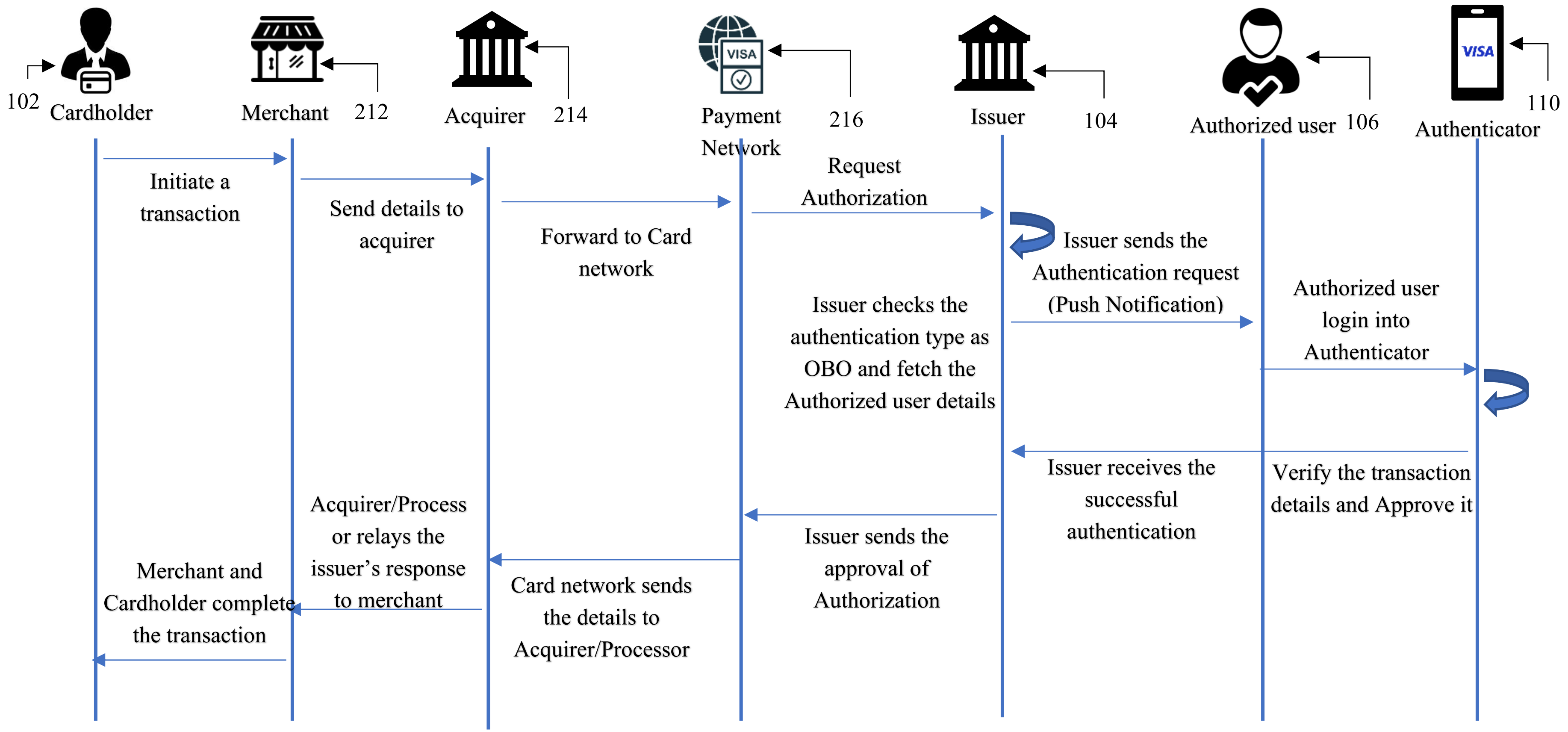

102
Cardholder
Issuer
104
Authorized User
106
Issuer App
108
Authenticator App
110
1
2
3
4
5
6
7
8
9

Figure 1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Merchant 212
Acquirer 214
Payment Network 216
Issuer 104
Authorized user 106
Authenticator 110
Initiate a transaction
Send details to acquirer
Forward to Card network
Request Authorization
Issuer sends the Authentication request (Push Notification)
Issuer checks the authentication type as OBO and fetch the Authorized user details
Authorized user login into Authenticator
Issuer receives the successful authentication
Verify the transaction details and Approve it
Issuer sends the approval of Authorization
Card network sends the details to Acquirer/Processor
Acquirer/Process or relays the issuer's response to merchant
Merchant and Cardholder complete the transaction

Figure 2

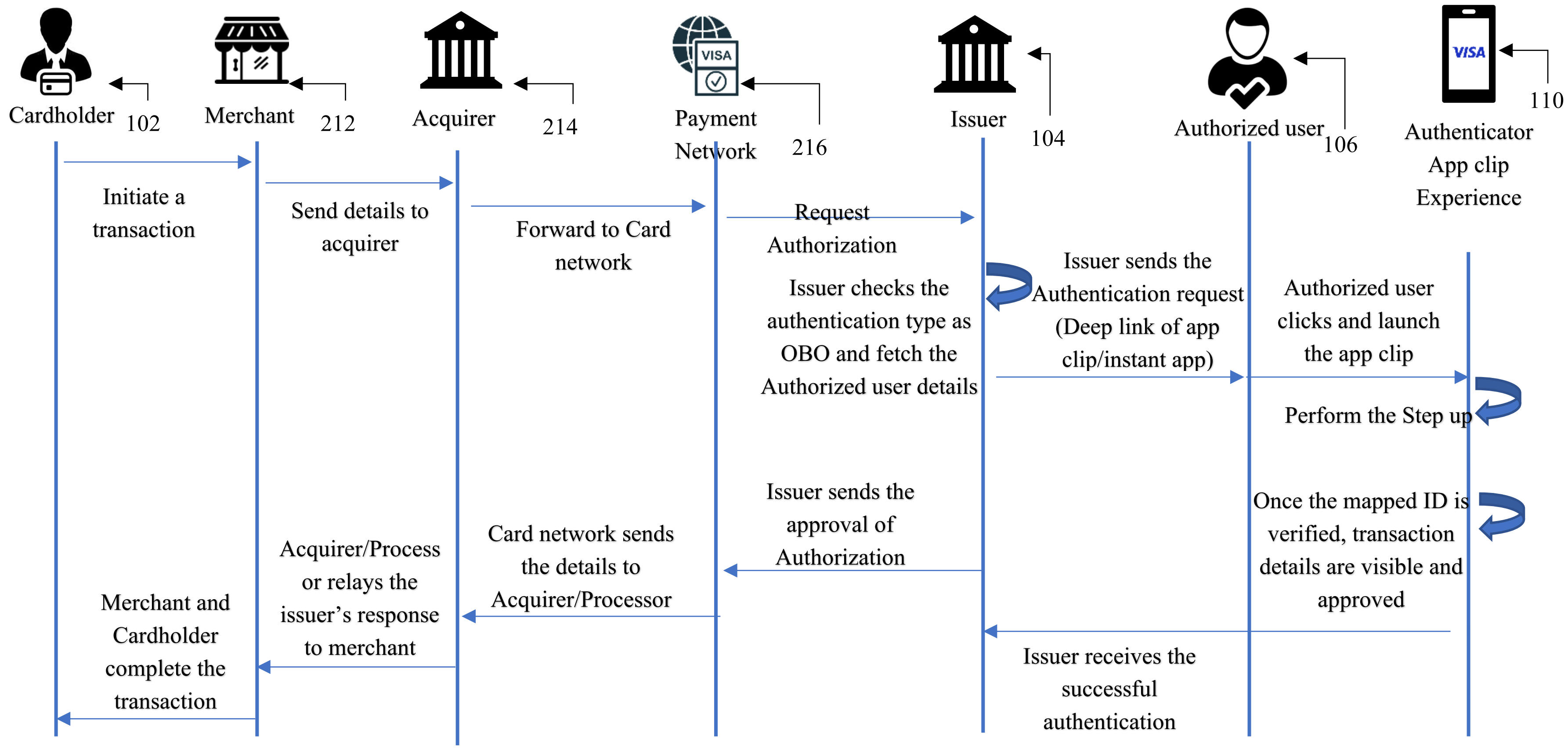
Cardholder
102
Merchant
212
Acquirer
214
Payment Network
216
Issuer
104
Authorized user
106
Authenticator App clip Experience
110
Initiate a transaction
Send details to acquirer
Forward to Card network
Request Authorization
Issuer checks the authentication type as OBO and fetch the Authorized user details
Issuer sends the Authentication request (Deep link of app clip/instant app)
Authorized user clicks and launch the app clip
Perform the Step up
Once the mapped ID is verified, transaction details are visible and approved
Issuer receives the successful authentication
Issuer sends the approval of Authorization
Card network sends the details to Acquirer/Processor
Acquirer/Process or relays the issuer's response to merchant
Merchant and Cardholder complete the transaction

Figure 3