Comparing Variable Handling Strategies in BDI Agents: Experimental Study

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Abstract: BDI (Belief-Desire-Intention) agents represent a paradigm in artificial intelligence, demonstrating proficiency in reasoning, planning, and decision-making. They offer a versatile framework to construct intelligent agents capable of reasoning about their beliefs, desires, and intentions. Our research focuses on AgentSpeak(L), a popular BDI language, and its interpreter using late variable bindings. Unlike traditional interpreters, it defers substitution selection until execution, enhancing rationality by preventing premature, erroneous selections. To validate our approach, we conducted experiments in a virtual collectable card marketplace. We implemented a system that can use both late and early variable binding strategies, comparing their performance. In shared and independent experiments, the late bindings strategy outperformed the early bindings strategy, although overhead costs were observed. We also conduct a brief discussion of the situations in which it is appropriate to use late bindings given the structure of the declared plans.

1 INTRODUCTION

The Belief-Desire-Intention (BDI) (Rao and Georgeff, 1997) agents represent a popular paradigm in the field of artificial intelligence and autonomous systems. These agents based on Bratman´s theory (Bratman, 1987) of intentions are inspired by human cognitive processes and exhibit remarkable capabilities in reasoning, planning, and decision-making. This process is called *practical reasoning* and consists of two phases. The first phase called *deliberation*, decides what goals we want to achieve. The second phase known as *means-ends reasoning* decides how we are going to achieve these goals (Wooldridge, 1999). The BDI architecture offers a versatile framework for constructing intelligent agents capable of reasoning about their beliefs, desires and intentions. Beliefs represent not only the inherent state of the autonomous agent but also a comprehensive portrayal of the state of the external world in which the agent is situated. These beliefs collectively constitute the foundational substrate upon which the agent's decision-making processes are founded. Contrapuntally, desires represent the state of the world that the agent would like to achieve, delineating its pursuit of specific objectives. Intentions are the persistent and goal-oriented aspects of the agent's architecture, representing objectives toward which the agent has committed to directing its resources and subsequent actions. These three architectural components allow the autonomous agents to make rational choices in dynamic and uncertain environments.

Over the years, numerous implementations have emerged (in (Silva et al., 2020) you can find a systematic review of the BDI agent architectures up to the year 2020). Among the well-recognized ones that have played a significant role in the development of BDI systems, we can cite IRMA (Bratman et al., 1988), PRS (Georgeff and Lansky, 1987), dMars (d'Inverno et al., 1998) and 2APL (Dastani, 2008). From the modern systems, we can mention JACK (Winikoff, 2005) and JadeX (Pokahr et al., 2005).

Our work is based on the fundamental BDI language AgentSpeak(L) (Rao, 1996). Several dialects of this language have been developed, one of the most used and still evolving is the ASL language for the Jason system (Bordini et al., 2007). The principle of

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these systems is based on the choice of intention that the agent has to achieve its goals. A goal is a state of the system which the agent wants to achieve so goals can be viewed as an adopted desire. An agent has plans that are sets of instructions on how to achieve a goal or react to an event. Each plan that has been selected to achieve a goal can declare another (sub)goal, so the goals are hierarchically ordered. If the top-level plan that has been chosen to achieve a goal of an intention is achieved, then intention is also achieved.

The authors of the AgentSpeak(L) language introduced functions for event selection, a plan that will be used to achieve the goal selection, and intention selection, only in the abstract and introduced non-determinism into its functionality. Over the years, several approaches have been published to eliminate this non-determinism and improve the rationality of the autonomous agent. Several significant approaches are listed in the following section.

We chose a different path to increase the rationality of the agents. In our prior paper (Zboril et al., 2022), we introduced a new AgentSpeak(L) language interpreter, characterized by the utilization of late bindings of variables. The agent maintains a set of valid substitutions that remain continuously accessible in relation to the belief base. It defers the actual selection of a substitution until such a time when it becomes requisite, such as when the agent is about to execute an action. This approach aims to avoid the inadvertent selection of a substitution that could later prove invalid, thereby mitigating the risk of plan failure during execution. Subsequently, our attention was directed towards the design of the operational semantics (Vidensky et al., 2023) of such an interpreter.

In this paper, we discuss a practical implementation of the interpreter using variable substitution. The remainder is structured as follows. Section 2 contains brief summary of works aimed at enhancing the rationality of autonomous agents. In Section 3, working principles and key aspects of late variable bindings in our interpreter are described. Section 4 describes two experiments, together with a discussion of the results. Section 5 deals with when it is possible to convert a plan to another plan, and that the agent achieves the same flexibility with early bindings as with late bindings. The paper concludes with Section 6, where the conclusion and possible future work are described.

2 RELATED WORKS

Over time, researchers have explored diverse methodologies aimed at enhancing the rationality of autonomous agents. Significant attention has been directed towards the refinement of intention selection approaches. Typically, rational agents concurrently embrace multiple intentions, and the strategic selection of these intentions can facilitate the fulfilment of all intentions while mitigating potential conflicts.

For example, the authors of (Thangarajah et al., 2003) presented a mechanism allowing agents to identify and mitigate a specific type of adverse interaction, where the effects of one goal undo the conditions crucial for the successful pursuit of another goal. To detect these interactions, the paper proposes the maintenance of summary information concerning both definite and potential conditional requirements, as well as the resultant effects of goals and their associated plans. Work on this mechanism has continued and has been practically verified to bring benefits even though the cost of the additional reasoning is small (Thangarajah and Padgham, 2011). The mechanism is exemplified using *goal-plan trees* (GPTs), which can be regarded as a representation of intention within the context of BDI systems.

Researchers from the same university (Waters et al., 2015) developed two new approaches. The first approach, denoted as *enablement checking* takes into account whether a suitable plan could be found in the next step. The second one, referred to as *low coverage prioritisation* operates under the assumption that a plan that can be safely executed only in a limited set of possible knowledge base states should be preferred. The team of authors also increased the flexibility and robustness of an agent by relaxing a plan to a *partial plan* that specifies which operators must be executed but does not need to fully specify their order or variable bindings (Waters et al., 2018). Subsequently, an optimization method that involves adjusting both the ordering and variable binding constraints was introduced (Waters et al., 2021).

The CAN (Sardina and Padgham, 2011) language has made notable contributions to increasing the flexibility of the agent and robustness. One of its key innovations, among other things, is the introduction of a failure-handling system. During the plan selection process, other relevant plans are retained as alternative strategies. In the event of a (sub)goal failure, the language tries to select another plan from these alternative strategies.

Other researchers took a different path and introduced a meta-model which extends the BDI framework to accommodate the representation of concepts that the agent needs to select plans based on *softgoals* (typically long-term goals that influence the choice of plans) and preferences (Nunes and Luck, 2014).

State-of-the-art solutions for avoiding conflicts between intentions are approaches based on the

Monte-Carlo Tree Search (MCTS) method (Yao et al., 2014). The original approach has been improved by allowing the interleaving of primitive actions in different intentions and taking into account the dynamism of the environment and fairness when choosing an intention (Yao and Logan, 2016). However, the scheduler was only focusing on a single agent. Recently, the approach has been extended to use for multi-agent settings where the scheduler takes into account other agents´ intentions (Dann et al., 2020; Dann et al., 2021; Dann et al., 2022).

Despite the extensive historical background in the realm of BDI system development and the considerable volume of published literature that has contributed to enhancing the rationality of autonomous agents (the papers referred to in this section and others are summarized in (Bordini et al., 2021)), it is imperative to underscore that this domain of inquiry remains ongoing and evolving.

3 LATE VARIABLE BINDINGS

As previously mentioned, the languages and systems, based on AgentSpeak(L) (Rao, 1996), choose appropriate substitutions immediately during the plan selection phase. However, these substitutions may become invalid during the plan execution phase due to a change in the environment or potential conflicts with another intention in the use of limited resources. One approach to handling the selection of substitutions was introduced in the 2APL system (Dastani, 2008). This system offers the possibility to create rules that specify decision processes including the handling of substitutions.

Our approach (Zboril et al., 2022) is based on maintaining a set of all possible variable bindings and working with this set during the execution phase of a plan. When the step of the plan is executed, the set may be limited and some substitutions are removed. If at least one substitution remains in the set, the plan can continue in execution. We call the set of substitutions a context, and we have named this approach *late bindings*.

All important operations and functions for late bindings (Zboril et al., 2022) and the operational semantics of our proposed interpreter (Vidensky et al., 2023) have already been published. To recall and especially for the sake of completeness, we present the most important definitions and a short description of the deliberation and plan execution phases once more in this paper.

The basic operation of our approach is *broad unification*.

Definition 1. Broad unification, denoted as ρU, is formally defined as:

$$\rho U(p, PS) \stackrel{\text{def}}{=} \{mgu(p, p') : p' \in PS\}$$

The function maps the atom p and atom p' from the set of atoms PS to a set of all possible most general unifiers without variables renaming.

Since beliefs are in the form of atoms, the belief base (BB) is also a set of atoms. We use the broad unification function when we need a unification for a single atom that is valid in BB in any interpretation. The result of the function is a set of unifiers which we call a possible unifier set (hereafter referred to as *PUS*).

When a deliberation process selects a plan for an event, it is associated with a PUS with which the agent operates when it executes the plan. This PUS is called the plan context and is changed as the agent performs actions or achieves and tests goals. If an event is triggered during the execution of a plan, the context of that plan is associated with it, in which case we speak of event context.

Instances of plans and events that have an associated context are called *weak instances*. They are formally defined as follows:

Definition 2. A weak plan instance (WPI) is a triple $\langle te, \mathbf{h}, ctx\rangle$, where te is a plan's triggering event, $\mathbf{h} = h_1; h_2; ...; h_m$ is the plan's body, and ctx is the plan's context.

Similarly, we can define a weak event instance.

Definition 3. A weak event instance (WEI) is a triple $\langle evt, ix, ctx\rangle$, where evt is an event, ix is an identifier of the intention that raises the event (or *null* in case of an external event) and ctx is a context.

The deliberation phase works with weak instances in such a way that if there is a WEI, then a plan is relevant if its triggering event and the event of this WEI are unifiable concerning the WEI context. A plan is applicable if each context condition is satisfied in the current state of the agent's belief base. This means it is possible to find a PUS for each context condition and then unify them.

A selected plan is adopted as an intention. In the original system (Rao, 1996), an intention is defined as a stack of partially instantiated plans. The deliberation process finishes with the insertion of the plan with the corresponding intention structure.

In a system that uses late bindings, intentions must work with WPI and WEI.

Definition 4. The intention is a structure containing a WEI of a triggering event and a stack of WPIs. Formally, it is defined as follows:

$$\langle evt, ix, ctx\rangle[\langle te_1, \mathbf{h_1}, ctx_1\rangle \ddagger \langle te_2, \mathbf{h_2}, ctx_2\rangle \ddagger \ldots \ddagger \langle te_n, \mathbf{h_n}, ctx_n\rangle]$$

where the top of the stack is on the left and the elements of the stack are delimited by ‡.

If an external event occurs, in our case in the form of WEI, a new intention is created for it. However, if a new (sub)goal is created or an event is triggered during the execution of an intention, again as some WEIs, the selected WPI for that internal event is added to the top of the stack of the currently executing intention. For more details, we refer to our previous works (Zboril et al., 2022; Vidensky et al., 2023).

In order to correctly describe how a context modification is performed, we need to reintroduce two more definitions.

Definition 5. The merging operation, denoted as $\ltimes$, maps two substitutions to one substitution so that the substitution unifies two different atoms in two sets of atoms and is defined as follows:

$$\sigma_1 \ltimes \sigma_2 \stackrel{\text{def}}{=} \begin{cases} \sigma_1 \cup \sigma_2 & \text{iff } \forall [t_1/x_1] \in \sigma_1\ \forall [t_2/x_2] \in \sigma_2 (x_1 = x_2 \rightarrow t_1 = t_2) \\ \emptyset & \text{else} \end{cases}$$

This operation can be used to merge two unifiers. If we want to modify a context with respect to another context, we need to find all the pairs that produce a non-empty set. The following definition is used for this purpose:

Definition 6. The restriction operator, denoted as $\sqcap$, returns a set of unifiers that contain all the most general unifiers that unify p_1 in PS_1 and p_2 in PS_2 is defined as:

$$\rho U_1 \sqcap \rho U_2 \stackrel{\text{def}}{=} \bigcup_{\sigma_1 \in \rho U_1, \sigma_2 \in \rho U_2} \sigma_1 \ltimes \sigma_2$$

where ρU_n is a simplified form of notation for $\rho U(p_n, PS_n)$.

For a more detailed description of this operation, please refer to our previous papers.

During the execution phase, the context can be modified at any step. When the goal test is executed, the context is restricted to retain only those substitutions for which the tested formula is a true belief. In the case of the test goal *?g(t)*, we can define the context modification as: $ctx_1 = ctx \sqcap \rho U(g(t), BB)$. The belief base ($BB$) is a set of atoms, therefore it can be used for broad unification.

After the successful execution of the achievement goal, there was probably a change in the belief base. The context of the plan that triggered the goal must adequately react to these changes before continuing the execution of the plan body. Also in this case the context modification is done by a restriction operation. When an agent is about to execute an action, it must create a ground atom for the action before executing it. Thus, all free variables must be bound to a specific atom. Consider an action of the format $a(\mathbf{t})$, where $\mathbf{t}$ is a term (atoms or variables). After the action is executed, all variables from term $\mathbf{t}$ are uniquely bound to the same variables in all substitutions in the context.

3.1 Interpreter Overheads

Preserving context entails additional computational costs for the agent's interpretation. In our previous research, we did not address these computational overheads, despite their significance in evaluating the appropriateness of using an agent interpretation featuring late bindings.

When we consider a WPI $\langle te, \mathbf{h}, ctx\rangle$, created using plan $P = te : b_1 \wedge \ldots \wedge b_n \leftarrow \mathbf{h}$, substitutions within the context can bind variables from this plan. These variables may be part of the triggering event, context conditions, or the body of the plan. However, it is crucial to note that the maximum number of variables that can be bound in this manner is limited to $|Var(P)|$. These bound values can be viewed as resources allocated by the agent (Waters et al., 2021).

Late bindings, as a strategy, allow for deferred resource allocation, maintaining a set of potential resources that can be bound to a particular variable. These potential resources remain in the set until the agent requires the use of a particular resource. It is important to highlight that this resource set is constructed within our system and, in accordance with (Vidensky et al., 2023), it is created only when the agent performs testing of its BB. In the case of other internal actions, such as the addition or removal of atoms from the BB, as well as external actions (henceforth referred to as "acts"), the execution of these actions can yield only one answer. This answer takes the form of free variable substitution within the atom that defines such actions within the plan.

According to Definition 1, the result of a broad unification is a set of substitutions denoted as $\rho U(p, BB) = \{\sigma_1 \ldots \sigma_n\}$. We assume that the agent's belief base BB contains only ground atoms and thus every element of $\rho U(p, BB)$ is a ground substitution.

The cardinality of $\rho U(p, BB)$ is inherently constrained by the cardinality of BB, leading to the conclusion that $|\rho U(p, BB)| <= |BB|$. The range of values to which variables from $Var(p)$ can be bound is, therefore, determined by the cardinality of BB.

Results arising from agent actions are added into the context through restriction with the original WPI context before act execution. Nevertheless, the definition of the restriction operation, as per Definition 6, posits that no new element (resource) can be added to this merged set. The set can either remain unchanged or be reduced to one of its subsets. This deliberation leads to the conclusion that the maximum cardinality of the set for a variable is dictated by the cardinality of the smallest set of answers to an act in which that variable was used.

As previously indicated, the only type of act for which such a cardinality can exceed one is the test goal. Consequently, the maximum possible cardinality of the context within a WPI, created through the execution of plan P, is $M^{|Var(P)|}$. Here, M denotes the largest cardinality observed within the set of answers to all previously executed test goals, encompassing all plans that are either currently in progress or have already been completed within the intention to which this particular WPI belongs.

4 EXPERIMENTAL EVALUATION

In this section, we compare the performance of the interpreter that uses late bindings versus the interpreter that uses an early bindings strategy. The system, which we named the Flexibly Reasoning BDI Agent (FRAg) [1], that will perform the interpretation was developed in the SWI Prolog [2] environment. The Prolog language naturally supports working with predicates, unifications, and substitutions, so it was a logical choice for implementing a system that supports the late bindings strategy. The system does not interpret programs written directly in AgentSpeak(L), but programs written in its dialect, which we designed to be easily interpreted using the Prolog interpreter. Agents can interact within an environment connected via an interface of this system. During each cycle, agents receive perceptions in the form of add and delete lists, based on which they adjust their belief base. Throughout the agent cycle, agents process inputs, perform practical reasoning and execute actions if possible.

4.1 Experimental Environment

To compare early bindings and late bindings strategies, we created a virtual marketplace environment. The goods traded in this marketplace are collectable cards. Each card has a trade price. However, as is common in marketplaces, the final price is determined by how much sellers are willing to sell a card for and whether any buyer is willing to accept that price. Buyers and sellers come to the marketplace with the intention of buying or selling one particular card. If they do not succeed within a certain period of time, they leave in disappointment. Agents in this marketplace act as resellers. Their job is to find a seller who sells a certain card and a buyer who wants to buy that card and is willing to make a deal. More concretely, whether sellers and buyers reach an agreement and make a transaction depends not only on the fact that they trade with the same type of goods but also on whether the seller's requested price is below the buyer's maximum acceptable price.

Sellers and buyers enter and leave the marketplace while the system operates, so the environment is naturally dynamic. We have modelled the above-described scenario by assigning each card an initial price, and both the seller and the buyer reduce this price using a coefficient generated in the range $\langle 0,1 \rangle$ according to a normal distribution with certain parameters (mean and dispersion), μ_B, σ_B, and μ_S, σ_S. We will use the indices S for sellers and B for buyers. The arrival of customers to the marketplace (buyers and sellers) is modelled according to a Poisson distribution with mean values λ_B and λ_S. Customers stay until they are serviced but for a maximum of a predetermined number of episodes, d_B and d_S. This duration is measured in episodes.

4.1.1 Illustrative Example

In this subsection, we illustrate a scenario in which the late bindings strategy has an advantage over early bindings. A plan for an agent looking for a matching offer to a demand can be written, in AgentSpeak(L) language, as:

```
+!sell :wants(Buyer, CD, Max_Price)
  <- ?offers(Seller, CD, Price);
     Price<=Max_Price;
     sell(Seller, Buyer, CD, Price)
     !sell.
```

In this illustrative example, there will be only one seller *adam* and two buyers *betty* and *clara* who want to buy the card that *adam* is selling. Consider that the set of base beliefs is given by

```
offers(adam, cd1, 85).
wants(betty, cd1, 60).
wants(clara, cd1, 90).
```

In Figure 1, the left side shows the execution of the plan by an interpreter using the early bindings strategy. In this context, it is assumed that the interpreter selects beliefs in the order of their insertion into

[1] https://github.com/VUT-FIT-INTSYS/FRAg
[2] https://www.swi-prolog.org/

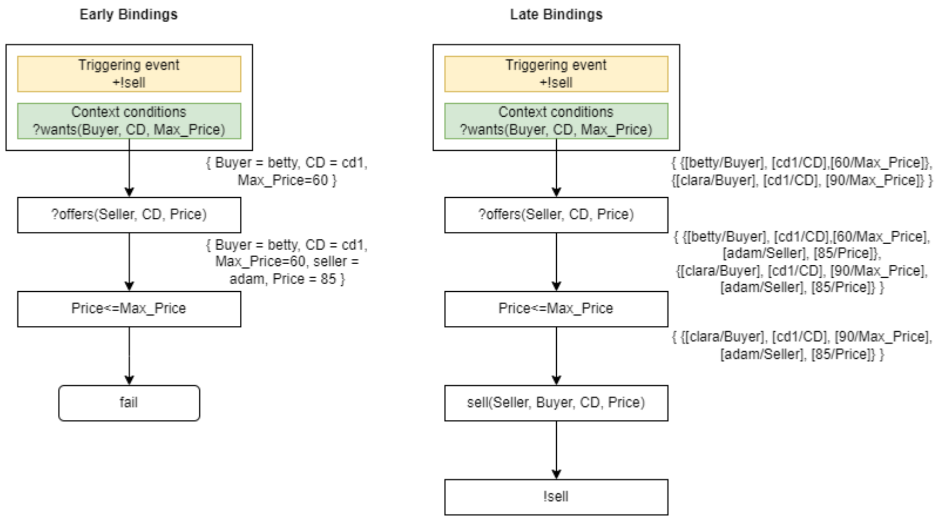


Figure 1: Illustrative example executed by interpreters using early and late bindings strategy.

the belief base. The interpreter successfully binds the variables for the context conditions and for the test goal. However, the price at which the card is sold is higher than the maximum price the buyer is willing to pay, so the result of the comparison is not true. At this juncture, the execution of the plans becomes unfeasible, leading to failure. The interpreter must execute the plan again from the beginning. On the second attempt, it would select *clara* as the buyer and be successful.

In the event of plan execution by an interpreter using the late bindings strategy, the aforementioned failure scenario can be preempted. As illustrated in Figure 1 on the right side, this interpreter systematically maintains a set of all possible substitutions. These substitutions are unified with new substitutions for other variables that appear during the execution of the body of the plan. If it is necessary to compare the *Price* variable against the *Max_Price*, the interpreter strategically reduces the context and retains only those substitutions for which this comparison is true. Therefore, the substitution that substituted *betty* for *Buyer* is removed. Before the action is performed, substitutions are applied and execution of the plan succeeds.

This example clearly illustrates that the use of late bindings serves as an effective preventive measure against both failure and the necessity for redundant plan executions. But whether this strategy will actually perform better remains to be proven experimentally.

4.2 Experiments

To compare both strategies, we conducted two experiments. In the first experiment, two agents were placed in the marketplace, each of them following a different strategy. In this experiment, agents competed among themselves to see who could make more deals. In the second experiment, agents operated independently.

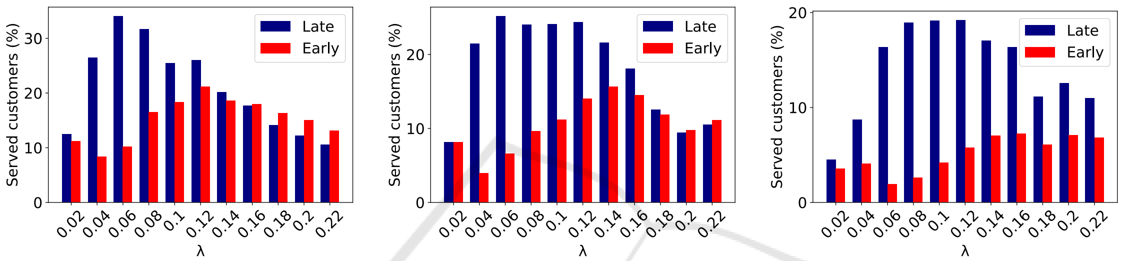
All experiments were run on the same personal computer equipped with AMD Ryzen 5 6600U processor (6 CPU cores and 12 threads) and 16 GB of RAM.

4.2.1 Experiment 1 - Competition

In this experiment, two agents, using different binding strategies (*Early* and *Late*), compete to find more pairs that want to trade the same card and make a deal. A fixed value of 0.2 was experimentally chosen for the parameters σ_B and σ_S. Parameters λ_B and λ_S were always set to the same value, within the range of 0.02 to 0.22 with a step size of 0.02. The remaining two parameters, μ_B and μ_S, were set to values in the range of 0.4 to 0.6 with a step size of 0.1. In this experiment, there are 8 different types of cards with which customers can trade. Customers leave the marketplace if they have not been served after 100 episodes, thus $d_B = d_S = 100$. We have also set the number of episodes at which customers are added to the system (and agents receive information about their presence from the environment) to a constant value of 750. Additionally, the number of episodes has been fixed at 5000 to ensure agents have the opportunity to serve clients who arrive later. The length of one episode was set to 0.5 milliseconds, and it was experimentally determined that this was sufficient time for both

Table 1: Results of the comparison of both strategies working together in one environment.

	$\mu_B = 0.4$; $\mu_S = 0.6$		$\mu_B = 0.5$; $\mu_S = 0.5$		$\mu_B = 0.6$; $\mu_S = 0.4$	
λ	Late	Early	Late	Early	Late	Early
0.02	12.45	11.19	8.11	8.11	4.51	3.58
0.04	26.43	8.32	21.48	3.97	8.74	4.07
0.06	**34.00**	10.21	25.14	6.60	16.34	1.92
0.08	31.71	16.46	23.99	9.60	18.91	2.60
0.10	25.47	18.28	24.12	11.2	19.16	4.17
0.12	25.98	**21.13**	24.34	14.05	19.19	5.79
0.14	20.15	18.63	21.61	15.65	17.05	7.03
0.16	17.72	17.95	18.08	14.52	16.37	7.25
0.18	14.13	16.27	12.56	11.87	11.14	6.10
0.20	12.2	15.05	9.41	9.75	12.55	7.10
0.22	10.57	13.12	10.53	11.09	10.96	6.81



(a) μ_B=0.4; μ_S=0.6. (b) μ_B=0.5; μ_S=0.5. (c) μ_B=0.6; μ_S=0.4.

Figure 2: Competition experiment. Average percentage of served customers for the parameter variants used to generate the price reduction coefficient.

agents to complete their tasks on the device where the tests were run. During the interpretation of the early bindings strategy, substitutions are selected randomly instead of taking them from the first answer, which is usual. This choice is made to avoid a high failure rate.

Table 1 shows the outcomes of the first experiment. For each parameter combination, the experiment was repeated 50 times, and the average percentage of customers served by each agent was computed. The best results for each agent are highlighted in bold. It is clearly visible that the late bindings strategy exhibits superior performance compared to the early bindings strategy across most parameter settings. The early strategy outperforms the late strategy only in scenarios where sellers reduce prices either equally or more than buyers, while concurrently witnessing a higher arrival of customers into the marketplace. This can potentially be attributed to the interpreter using the early bindings strategy having an increased likelihood of randomly selecting a seller willing to offer an equivalent or higher price than the buyer in such circumstances. Conversely, when buyers lower prices more substantially, the late strategy consistently attains superior results relative to the early strategy. This discrepancy is attributed to a considerably reduced probability of the agent randomly selecting a suitable seller for the buyer in this context.

Consistently, in the experiment, both agents achieved the best results when customer arrivals at the marketplace were frequent, and sellers reduced prices to a greater extent than buyers. Consequently finding a buyer who was willing to pay the price the seller was asking has become more likely. These observed trends are graphically illustrated in Figure 2. Note that even in the optimal case, not all customers, both buyers and sellers, can be served. A situation can and has arisen where for some customers there was no counterparty for them to trade with while they were in the shop.

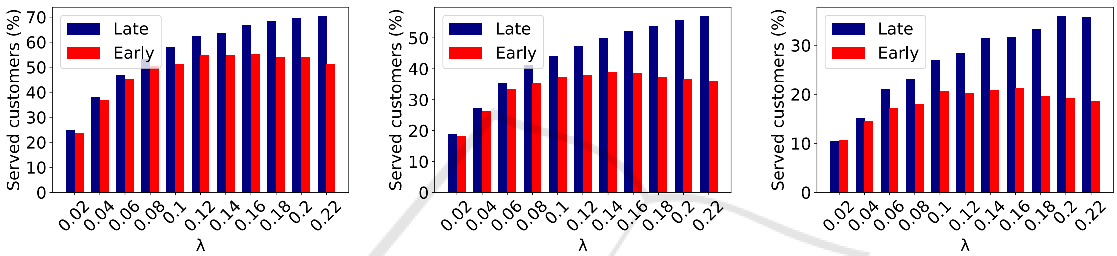
4.2.2 Experiment 2 - Independent Work

In this experimental setting, both agents operated independently, ensuring that the actions of one agent did not influence the outcomes of the other agent.

The experimental configuration closely resembled the preceding one, with the exception that the episodes were not time-constrained. Instead, each episode started at the moment when an agent perceived the environment again. Furthermore, each experiment was run 20 times and the number of episodes during which the agents operated was reduced to 1000. In this experiment, alongside assessing the average percentage of served customers, we also paid

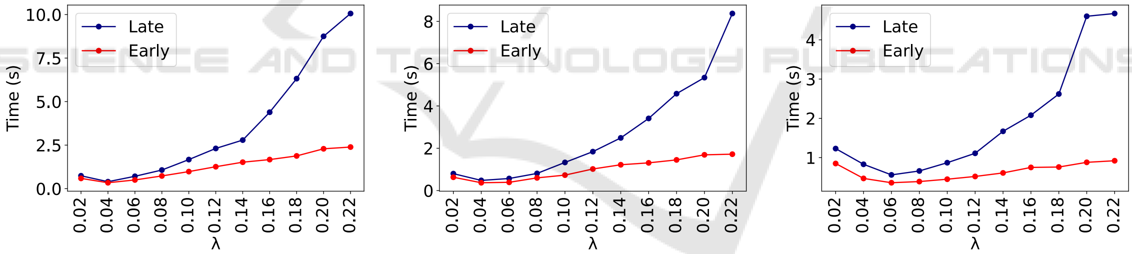
Table 2: Results of the comparison of both strategies working independently of each other. In parentheses are the average times the agent spent computing.

	$\mu_B = 0.4$; $\mu_S = 0.6$		$\mu_B = 0.5$; $\mu_S = 0.5$		$\mu_B = 0.6$; $\mu_S = 0.4$	
λ	Late	Early	Late	Early	Late	Early
0.02	24.83 (0.74)	23.83 (0.59)	18.88 (0.80)	18.21 (0.63)	10.51 (1.23)	10.60 (0.85)
0.04	37.89 (**0.40**)	36.88 (**0.34**)	27.28 (0.48)	26.46 (0.37)	15.15 (0.83)	14.48 (0.47)
0.06	46.94 (0.71)	45.09 (0.50)	35.49 (0.57)	33.57 (0.39)	21.10 (0.56)	17.11 (0.36)
0.08	53.40 (1.07)	50.61 (0.73)	41.15 (0.81)	35.33 (0.60)	23.00 (0.66)	18.03 (0.39)
0.10	57.86 (1.67)	51.41 (0.98)	44.15 (1.33)	37.22 (0.73)	26.93 (0.87)	20.57 (0.45)
0.12	62.40 (2.31)	54.76 (1.26)	47.42 (1.84)	38.08 (1.02)	28.45 (1.11)	20.30 (0.52)
0.14	63.69 (2.79)	54.96 (1.52)	50.00 (2.49)	38.90 (1.22)	31.52 (1.67)	20.89 (0.61)
0.16	66.79 (4.39)	**55.36** (1.67)	52.13 (3.41)	38.58 (1.31)	31.74 (2.08)	21.23 (0.75)
0.18	68.54 (6.32)	54.08 (1.88)	53.69 (4.58)	37.24 (1.45)	33.38 (2.62)	19.59 (0.76)
0.20	69.55 (8.75)	53.87 (2.29)	55.77 (5.34)	36.77 (1.69)	35.96 (4.60)	19.16 (0.88)
0.22	**70.42** (10.06)	51.13 (2.39)	57.08 (8.37)	35.94 (1.72)	35.70 (4.67)	18.57 (0.92)



(a) μ_B=0.4; μ_S=0.6. (b) μ_B=0.5; μ_S=0.5. (c) μ_B=0.6; μ_S=0.4.

Figure 3: Independent work experiment. Average percentage of served customers for the parameter variants used to generate the price reduction coefficient.



(a) μ_B=0.4; μ_S=0.6. (b) μ_B=0.5; μ_S=0.5. (c) μ_B=0.6; μ_S=0.4.

Figure 4: Independent work experiment. Average computation time for the parameter variants used to generate the price reduction coefficient.

attention to the computational time spent by the agent. To be specific, this measurement encompassed the entire duration from the initiation to the completion of the agent's interpretive loop.

The outcomes of the experiment are presented in Table 2, with the best results highlighted in bold. The effectiveness of the agents in serving customers is visually represented in Figure 3. When comparing these results with the results from the first experiment (Figure 2), noticeable differences are evident.

Notably, the differences between the agents are less pronounced compared to the scenario in which their actions could influence each other. Both agents again achieved the best results under conditions where customer arrivals were frequent, and sellers reduced prices to a greater extent than buyers. This outcome aligns with expectations, as it is inherently more feasible to find a buyer in such circumstances.

Figure 4 presents a graphical representation of the computational time consumed by the agents. The charts show that for the agent using an early binding strategy, the increase in computational time relative to the number of customers is slow due to its reliance on random selection, as previously explained.

Conversely, the results for the agent using the late bindings strategy reveal a significant increase in computational time. This is attributed to the agent's active management of the set of substitutions, with the cardinality of this set expanding proportionally to the growing number of customers present in the marketplace.

In the experiment, the agents exhibited the shortest computational times when sellers reduced prices more than buyers, and customer arrivals at the marketplace were very slow. We infer that this can be attributed to the smaller customer pool, which facilitates the rapid finding of feasible pairs. However, this circumstance may also result in the absence of such pairs, consequently rendering the agents incapable of proceeding with their tasks.

5 FLEXIBILITY OF EARLY BINDINGS AT THE LEVEL OF LATE BINDINGS THROUGH PLANS MODIFICATIONS

In this section, we want to discuss several situations where it is appropriate for an agent to use late bindings and also when it is possible to modify the plan in a way that gives the agent the same flexibility when using both late and early bindings.

Our selected example showcased the application of late and early variable binding in a program executing two distinct queries within separate interpretation cycles. The plan used in this program could be phrased as: *"The agent, if there is a customer or customers, will find out their requirements, check whether they can be met and, if necessary, execute the deal"*. In essence, the agent periodically solicits information about customer's preferences and seller's offerings. This simple example could be rewritten, however, since we assume that the agent has data for both queries at the same time. Then it would still work the same way for an agent executing a plan

```
+!sell :wants(Buyer, CD, Max_Price)
       & offers(Seller, CD, Price)
       & Price <=Max_Price
  <-Sell(Seller, Buyer, CD, Price);
       !sell.
```

In this case, the problem of finding the buyer and seller is solved implicitly by evaluating contextual conditions. In general, we see an incentive to use late bindings in agent execution when an action is or can be performed between two test goals, i.e., the two test goals are performed at different points in the agent's interpretation.

In the following paragraphs, we show cases where an agent has reason to execute test goals in different cycles, and what it would take to convert such a plan to one that addresses the problem of possible bad binding choices in an early bindings strategy.

I. By using goal testing we may want to guarantee the agent's safe execution of the plan. Usually, this involves ensuring that resources are available before the action is executed, but it can also be tested that some resources will be available after the action or actions are executed. In the latter case, the next action does not determine a particular resource for the subsequent execution of the action. For example, if we have a plan that involves travel, the agent, given knowledge of a car in the garage, may proceed to inspect whether any of the cars are operational. If not, the agent has the flexibility to choose an alternative activity. Such a plan could include a body with a sequence of acts as shown below. Here, the body of the plan is shown as some part of it, and to illustrate this we show three dots before and after such a part.

```
... ?is(garage, Car); goto(garage);
    ?mobile(Car);
    !go(Car, Destination) ...
```

In this particular example, we can assume that the agent can re-execute the first test goal immediately before executing the second test goal. For example, such a transformation to a program that guarantees flexible behaviour even when using an early binding strategy would look like the following.

```
... ?is(garage, Car); goto(garage);
    !mobile(Car2);
    !go(Car2, Destination) ...

+!mobile(Car):
   ?is(garage, Car) & ?mobile(Car).
```

II. In the usual way of processing environmental perceptions, which was used for example in the MAPC2022 (Ahlbrecht et al., 2023) competition, the agent's belief base changes according to the provided add and delete lists as a result of the perception of the environment. Then, if the agent needs to store the perceptions for future use, it can bind a variable to the perception of interest and use this binding when it has all the necessary information. To demonstrate this, we will use a slightly different example than the one used in the previous section. The agent observes signs along the way that may help determine how to proceed in the future. The following part of the body of the plan demonstrates such an agent that, while observing the environment at one location, remembers the sign seen by binding it to the variable *Sign*, which it then uses at a crossroad to decide which path to take next.

```
... ?sees(sign, Sign);
    goto(crossroad);
    ?sees(Destination, Sign);
    goto(Destination) ...
```

However, if it saw more than one sign in the first location, only one would be bound to the variable when using the early bindings strategy. But then the *Destination* would not necessarily be marked with this *Sign*, but with another one that it also saw in the first place, however, this *Sign* was not selected for binding. In the case of late bindings, the agent interpreter stores all these signs in context and, by restriction operation (Definition 6), selects a *Destination* based on the signs if it matches one of these signs. In the case of early bindings, this situation could again be handled by re-querying the agent using a sub-plan in which an evaluation similar to the one in the previous section would be performed in the context conditions. However, before doing so, it would be necessary to store all previously seen tags in the agent's idea base.

III. The previous two problems can be solved by correctly changing the plan's design or plans, but the programmer is responsible for the required functionality of the agent. The third argument for the use of late bindings concerns the declaration of plans as such if these plans can be chosen during consideration for a WEI that has a non-empty context. That is, some variables in the triggering event of such a WEI may already have predetermined possible resources that were created sometime earlier during the execution of the intention under which this WEI was created. The repetition of the query according to **I** and **II** is more difficult. This is because the programmer would need to know what queries over what beliefs were executed during the execution of that intention.

These three examples show situations where the programmer must be aware of the problems that can arise when using an early bindings strategy. In the third case, where a plan can be used as a sub-plan within an intention, such a transformation would predetermine how the variables that are used as input must be bound in the intention.

6 CONCLUSIONS

In this paper, we have extended our previous work by introducing an implementation of a system capable of using both late and early variable binding strategies. These two approaches were experimentally compared within the context of a virtual collectable card marketplace. The primary goal for agents in this dynamic environment was to find buyers for sellers willing to buy cards at specified prices.

Two experiments were conducted. In the first experiment, two agents, each using distinct variable binding strategies, operated on a shared marketplace. The agent using the late binding strategy outperformed the second agent across most experiment parameters. In the second experiment, where agents operated independently, the late binding strategy also yielded better results, albeit with smaller differences in performance.

It is worth noting that our approach has inherent limitations. The maintenance and modification of a set of potential substitutions (context) introduce overhead costs for the interpreter. These costs were discussed and were evident in the results of the second experiment, where we also focused on computing time. For the late binding strategy, computational time increased significantly relative to the parameter determining the rate of customer arrivals at the marketplace. With each additional customer, the size of the context was increased. In contrast, the agent using the early binding strategy managed to work with only a slight increase in computation time. While it is theoretically possible to reduce this overhead by using other algorithms or modifying the current code, it remains an intrinsic aspect of this approach.

Further enhancements to the system, beyond the reduction of overhead costs, including the improvement of the user experience. Currently, the system interprets the dialect of the AgentSpeak(L) language developed by us. We are actively working on a compiler for this language and its integration with a user interface.

Future research directions involve the development of intention-selection algorithms. In this domain, the state-of-the-art approach is based on the Monte Carlo Tree Search (MCTS) method. We intend to incorporate this method into our system and combine its advantages with those of the late variable binding strategy. In addition, we intend to explore the possibility of using this approach to detect similarities between intentions that could lead to coordinated or concurrent execution of such intentions or to decide on the choice of specific variable bindings in order to synthesize such intentions.

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