Appendix

Appendix A

Literature Search on Decision Making and Aging

Original articles in the area of decision making and aging were identified using systematic literature review methods (Devillé, Buntinx, Bouter, Montori, de Vet, van der Wint, & Bezemer, 2002; Cook, Mulrow, & Hayne, 1997; see Fellows, Heberlein, Morales, Shivde, Waller, & Wu, 2005, for a specific example in a domain other than decision making). Systematic literature review involves three main search strategies for finding relevant studies concerning a topic of interest: 1) computer-aided search in common scientific databases using a specific set of keywords; 2) extensive search in specific journals that are known to publish articles related to the topic of interest; 3) examining the reference sections of primary studies identified in the automated search as well as those of known literature reviews. These strategies are complementary and can be performed iteratively to make searches more constrained by focusing on particular topics or even authors. Following the identification of potentially relevant papers, one reviewer (or more) can screen the titles and abstracts of the identified publications to insure the appropriateness of the study for inclusion in the narrative or quantitative analysis.

In the following search on decision making and aging a combination of these tactics was used. The main goal of the search was to identify articles that met three criteria: (1) were original research articles with empirical evidence; (2) investigated both young and older adults; (3) reported results on multi-attribute, multi-alternative decision making tasks. However, for the purpose of reviewing the aging and decision-making literature more generally, other empirical papers, review articles, and meta-analysis concerning decision-making were also considered. Additionally, papers concerning strategy use and selection in other domains were taken into account so that they could be used for comparison purposes.

Automated search. Searches were conducted in the PsycINFO database. One general search strategy was developed to identify articles that referred to "decision making" (and a variety of decision making related terms) and "aging" in the title, the abstract, or used the term as keyword or subject heading. The key terms used for the computer database search were decision making, judgment, aging (age, age differences, age groups), and strategy (strategies, heuristic). These searches were then limited to peer-reviewed journal articles concerning adult human subjects, with abstracts, in English, from the years 1872 to 2005 (June). Table A.1 summarizes the results of the automated search.

Table A.1: Number of Hits Identified in the Automated Search using PsycINFO (1872-2005, June)

Domain	Number of Papers
Decision Making	30367
Aging	145862
Decision Making AND Aging	2986
Decision Making AND Aging AND Strategies	219

The results of the automated search were hand-reviewed by the investigator to identify the articles that met the three criteria listed above. From the 219 articles identified, only 5 were directly concerned with age-comparisons between young and older adults in decision making tasks (Capon, Kuhn, & Gurucharri, 1981; Chen & Sun, 2003; Johnson, 1993; Kim & Hasher, 2005; Riggle & Johnson, 1996). Furthermore, only 3 of these papers were concerned with multi-attribute, multi-alternative decision making tasks (Capon, Kuhn, & Gurucharri, 1981; Johnson, 1993; Riggle & Johnson, 1996). Thus, although as suggested in table A.1, there is a considerable number of papers addressing decision making and/or aging most are not concerned with age differences in the use of decision strategies.

Other papers focused on age differences in strategy use in arithmetic tasks, associative learning tasks, covariation detection tasks, probability reasoning tasks, and confidence judgments. The remaining articles pertained to other age-groups (e.g. children), or focused on different topics such as health intervention strategies, or educational strategies. To increase the number of hits concerning multi-attribute, multi-alternative decision tasks ad hoc searches for publications by the same authors were conducted. This produced four other papers authored or co-authored by Mitzi Johnson (Johnson, 1990, 1997; Johnson & Drungle, 2000; Stephens & Johnson, 2000) and one paper co-authored by Lynn Hasher (Tentori, Osherson, Hasher, & May, 2001).

Manual search. A manual search through the abstracts of the *Psychology & Aging* journal (1990-June 2005) was conducted in order to find articles that concerned decision making and had not yet been encountered using the automated search. Three such papers were identified (Finucane, Mertz, Slovic, & Schmitt, 2005; Spaniol & Bayen, 2005; Zwahr, Park & Shifren 1999). Additionally, a meta-analysis concerning everyday-problem solving and decision making abilities emerged (Thornton & Dumke, 2005). An ad hoc PsycINFO search for publications by the same authors produced 2 additional papers (Finucane, Slovic, Hibbard, Peters, Mertz, & Macgregor, 2002; Hibbard, Slovic, Peters, Finucane, & Tusler, 2001).

Inspection of references. Three review articles (Peters, Finucane, Macgregor, & Slovic, 2000; Sanfey and Hastie, 1999; Yates & Patalano, 1999) were obtained from analyzing the references of the papers identified in the automated and manual searches. The references of these review articles, one meta-analysis (Thornton & Dumke, 2005), and the other papers of interest were then searched for other potentially relevant papers. Using this method one other paper concerning age differences in decision making was identified (Streufert, Pogash, Piasecki, & Post, 1990). Additionally, some papers were found which focused on issues potentially related to decisions between alternatives, such as age differences in multiple-cue probability learning (Chasseigne, Grau, Mullet, & Cama, 1999; Chasseigne, Ligneau, Grau, Le Gall, Roque, & Mullet, 2004).

Appendix B

Using Elementary Information Processes (EIP) to Quantify the Cognitive Demand of TTB, Take Two, and FR Strategies

One assumption underlying different theories of decision making is that strategies differ in regards to the cognitive costs they impose on decision makers (e.g., Beach & Mitchell, 1978; Gigerenzer et al., 1999). Payne, Bettman and Johnson (1988; 1993) were perhaps those who better articulated this idea and formalized the cognitive costs imposed by different decision rules. They proposed that decision rules share a number of basic components that combine to produce a strategy, for example, READ, a component responsible for reading attributes into memory, and DECISION, a component responsible for choosing an object (see Table 1.2 in Chapter 1 for a more detailed enumeration and description of EIP). In what follows, I report how I used the EIP framework to quantify the cognitive demands of each strategy considered in Studies 1, 2, and 3.

Method

I computed the number of operations each decision rule involves to quantify the cognitive effort associated with the use of different decision strategies considered in the study. The EIP considered were those common to the three different strategies: READ, COMPARE, GUESS, and DECISION[1]. Thus, for example, per cue looked up, TTB required reading into a memory store two cue values associated with each of the two options (READ), comparing these two (COMPARE), and provided that this cue discriminates, making a decision (DECISION). If the cue did not discriminate, another two cue values were read and compared, and so on until a decision was made or no more cues were available, leading the algorithm to choose randomly (GUESS) between the two options.

Results

The tallies for the three different strategies considered in the three Studies are presented in Table B.1. An inspection of this table shows a clear difference between strategies, with TTB being the least effortful and FR the most effortful. Moreover, this pattern

[1] Please note that this provides lower estimates concerning the cognitive demand of FR because this strategy implies additional components, namely, multiplication and addition components. Nevertheless, using the shared building-blocks provides an illustrative ranking of cognitive demand of strategies.

is constant across the three studies. These results represent an illustration of the different cognitive demands implied in the use of TTB, Take Two, and FR.

Table B.1: Elementary Information Processes Counts (M and SD) for the All Trials of Studies 1, 2, and 3 as a Function of Decision Strategy

	TTB		Take Two		FR	
Study	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	259.32	14.93	582.50	22.05	904.86	4.89
2	263.96	8.36	573.82	15.91	902.01	2.03
3	266.57	8.43	573.30	17.54	901.80	2.05

Discussion

The predictions of Studies 1, 2, and 3 are based on the premise that different strategies impose different demands on the decision maker. The EIP counts support this assumption by providing a remarkable demonstration of the different number of operations required to perform the decision task when using TTB, Take Two, and FR. While TTB provides a frugal solution to deciding between objects, comparatively, Take Two requires twice as many operations. In turn, FR's demands are roughly double those of Take Two.

Appendix C

Using Model Recovery Methods to Test the Accuracy of an Outcome Only vs. an Outcome and Search Classification Methods

The use of classification methods that take both decision makers' choices and their information search patterns into consideration has been often called for (Einhorn, Kleinmuntz, & Kleinmuntz, 1979; Einhorn & Hogarth, 1981; Pitz & Sachs, 1984). The intuitive appeal of using an outcome and search classification method is its promise in providing a complete and accurate classification of participants. However, it is an empirical issue whether an outcome and search classification method is superior to an outcome only one which considers only individuals final choices. To provide an answer to this question I used model recovery techniques. Model recovery techniques involve 1) generating data on the basis of a known process or distribution, usually adding some variance to its outcome, 2) using some method of interest to identify the underlying structure of the data, and 3) comparing the resulting structure to the known distribution underlying the data to obtain an estimate of the accuracy of the classification process (see Pitt, Myung, & Zhang, 2002, for a detailed example).

The general strategy adopted here was to determine how successful an outcome only and an outcome and search classification methods are at uncovering the strategies used by simulated participants. By using simulated participants one is able to control the underlying distribution of strategy users and thus quantify the success of different methods in recovering the true state of events. Naturally, if participants were to perfectly employ a particular strategy throughout all trials both classification methods should be equivalent. However, people make mistakes when employing decision strategies (Bettman et al., 1990) and thus one need to ask whether the two classification methods are equally reliable when considering different distributions and types of errors, such as errors in reading and comparing information, or making a decision.

Method

I first generated data for a number of simulated participants using one of 3 strategies, TTB, Take Two, and FR, by implementing the corresponding algorithms as computer programs. The algorithms simulating each of these strategies were implemented in a way that a probability with which a mistake would be made could be specified when using a particular component of the strategy. Strategies' components were defined according to Payne et al.'s

(1988, 1990) classification of elementary information processes (EIP). The components of interest were those common to all three strategies, 1) a storing component (READ), responsible for storing cue values in working memory, 2) a retrieval component (COMPARE), responsible for the retrieval and comparison of values in working memory, and (3) a decision component (DECISION), responsible for the choice of a particular option. The probabilities associated with errors in the different components at each time step were varied systematically from .05 to .5. An error in the storing component amounted to storing a cue value as 1 when it was in fact 0, and vice-versa. An error in the retrieval component consisted of not being able to judge a difference between options: This led TTB and Take Two strategies either to look up another cue if one was available or guess if it was not; for FR, which compares the values of the tallies of the two options after looking up all information, such a mistake always led to guessing. Finally, an error in the decision component was implemented as choosing the opposite object prescribed by the strategy. I considered types of errors independently, not allowing a particular set of simulated participants to make more that one type of error. All samples of simulated participants included 100 users of each strategy. The simulated participant's responses corresponded to the algorithms' responses to data from randomly selected input samples from Study 2.

Following the data generation, I used both an outcome only and the outcome and search classification methods to classify participants as users of a particular strategy. The outcome only classification procedure involved counting for each participant the number of inferences for which the final choice corresponded to that predicted by the different strategies. The outcome and search classification involved counting for each participant the number of inferences for which the information search *and* the final choice corresponded to the predicted search and choice by the different strategies. In both methods, the strategy that predicted most inferences correctly for a simulated participant was assigned to it.

Results

Figure C.1 shows the proportion of correctly classified participants as function of classification method, component in which error was introduced, and associated error probability. Overall, it is possible to observe that the classification based on outcome and search suffers little with increased probability of error regardless of type of component affected. When the DECISION component is considered no change at all is visible in performance. Also, when READ and COMPARE are considered the outcome and search classification only decreases performance slightly when probability of error reaches values close to .50. Regarding the outcome only classification method, in general, its performance declines steadily as a function of increases in probability of error. However, the two classifications are identical when lower error probabilities are considered, with differences between classification methods being noticeable only at levels of error above .20.

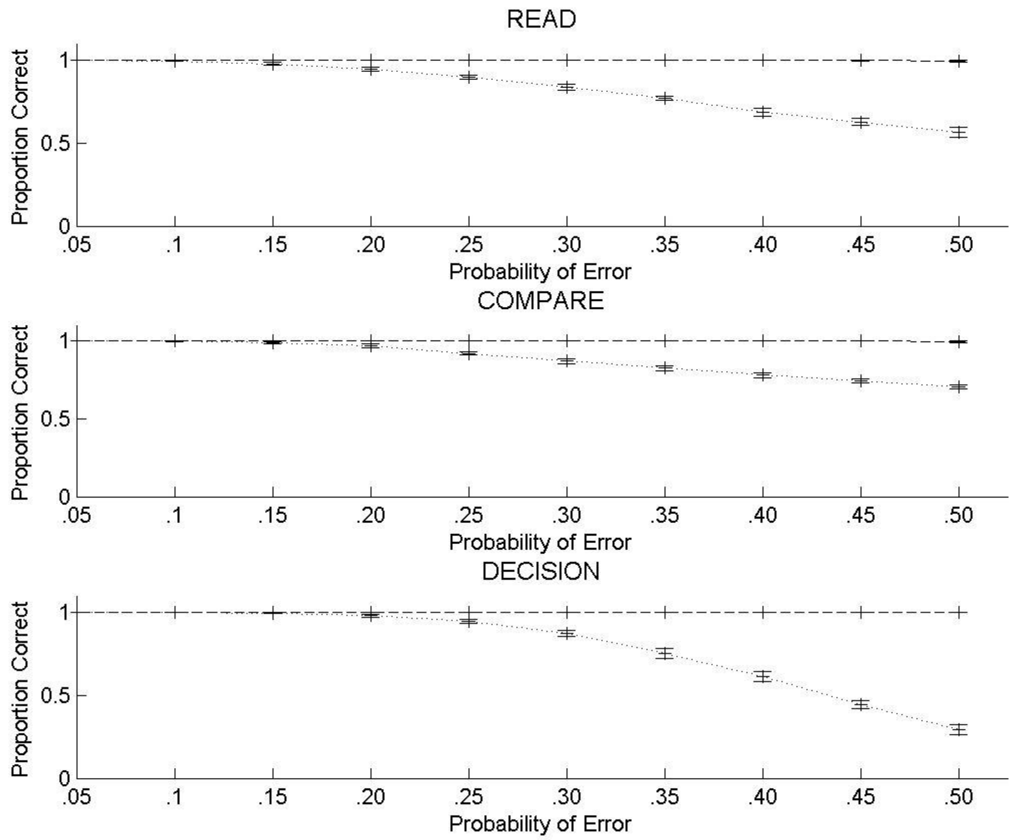

Figure C.1: Proportion of correctly classified participants as function of classification method, component in which error was introduced, and associated error probability.

Discussion

The results of using model recovery techniques to asses the accuracy of two classification methods suggest that an outcome and search method is more accurate than an outcome only one when participants make considerable amount of application errors.

The idea that individuals make mistakes when applying decision strategies is relatively common in the decision making literature (e.g., Bröder & Schiffer, 2003a, 2003b; Rieskmap & Otto, submitted) and has received empirical support (Bettman et al., 1990). However, little is know about the frequency with which decision makers apply strategies incorrectly. Bettman et al. (1990) reported that young decision makers choose incorrectly the option prescribed by a strategy 11% of the time. However, future work needs to be conducted to validate this estimate concerning the strategies analyzed here and, additionally, concerning an older population.

Appendix D

Summary of the Outcome Only Classification Results

Table D.1: Strategy Distributions in Studies 1, 2, and 3 according to an Outcome Only Classification.

	Study 1 ($N = 22$)				Study 2 ($N = 80$)				Study 3 ($N = 83$)			
	COMP		NONCOMP		COMP		NONCOMP		COMP		NONCOMP	
Strategy	*No.*	%	*No.*	%	*No.*	%	*No.*	%	*No.*	%	*No.*	%
TTB	1	9.1	3	27.3	1	2.4	18	46.2	8	19.5	22	52.4
Take Two	5	45.5	6	54.5	4	9.8	11	28.2	5	12.2	10	23.8
FR	3	27.3	—	—	35	85.4	7	17.9	22	53.7	9	21.4
Unclassified	2	18.2	2	18.2	1	2.4	3	7.7	6	14.6	1	2.4
Total	11	100	11	100	41	100	39	100	41	100	42	100

COMP = Compensatory Environment; NONCOMP = Noncompensatory Environment

Appendix E

Results of Multinomial Logistic Regression Analyses Based on the Outcome Only Strategy Classification Method for Study 2

The classification relying only on the final choices provided almost identical results as the one based both on outcome and search in the compensatory condition: only 1 (2.4 %) TTB user was identified, 4 participants (9.8 %) were identified as using Take Two, 35 (85.4 %) as FR, and 1 (2.4 %) was left unclassified. However, the results differed considerably in the noncompensatory condition, with 18 (46.2 %) TTB users being identified, 11 participants (28.2 %) classified as Take Two, 7 as FR (17.9 %), and 3 (7.7 %) being left unclassified. Thus, the outcome only classification identifies a larger proportion of participants relying on the noncompensatory TTB strategy in the noncompensatory condition than the outcome and search classification suggests. Interestingly, the results of the outcome only method match approximately those found by Bröder (2003) concerning TTB and FR. The use of model recovery techniques suggested that an outcome and search classification method provides superior classification compared to an outcome only one, which raises the possibility that the use of noncompensatory strategies has been overestimated in previous studies using outcome only classification procedures. Nevertheless, future studies using similar techniques should investigate this issue more deeply.

Concerning the effect of cognitive capacity on strategy use, I conducted multinomial logistic regressions to assess the predictive value of environment, each measure of capacity, and their interaction, on the use of strategies as classified based on the classification using only participants' choices. In general, the results based on the outcome only classification method converge with the outcome and search classification in showing a main effect of knowledge and an interaction effect of working memory. However, it contrasts with the latter by additionally revealing a main effect of resistance to proactive interference and interaction effects involving short-term memory and reasoning. An analysis of these interaction effects by splitting the conditions showed a remarkable similarity between classification methods. In the compensatory environment, effects of working-memory, short-term memory, and reasoning emerged, while in the noncompensatory condition, an effect of knowledge was detected. These results match those found using an outcome and search classification and fit the hypothesis that individual differences in cognitive mechanics play an important role in the compensatory environment, while intelligence, in particular, knowledge, is associated with the adaptive use of more frugal strategies in a noncompensatory environment.

Table E.1: Goodness of Fit of a Series of Multinomial Logistic Regression Models with Strategy Classification as the Dependent Variable

		G	*P*	Δ*G*	*P*
Step 1: Environment by itself		42.07	<.001		
Step 2: Environment + Capacity	WM	42.48	<.001	0.41	.815
	STM	43.42	<.001	1.35	.510
	SPEED	42.87	<.001	0.80	.671
	RPI	48.46	<.001	6.40	.041
	KNOW	51.04	<.001	8.97	.011
	REASON	43.52	<.001	1.45	.485
Step 3: Environment + Capacity + Environment*Capacity	WM	58.09	<.001	15.61	.001
	STM	54.87	<.001	11.45	.003
	SPEED	45.18	<.001	2.32	.314
	RPI	48.99	<.001	0.52	.770
	KNOW	51.35	<.001	0.31	.856
	REASON	49.69	<.001	6.17	.046

WM = Working Memory; STM = Short-term memory; RPI = Resistance to Proactive Interference; KNOW = Knowledge; REASON = Reasoning. In Step 2, Δ*G* represents the difference between *G* of the model with environment and cognitive capacity as predictors and that of the model with only environment as predictor. In Step 3, Δ*G* represents the difference between *G* of the model with environment, each capacity, and their interaction as predictors and that of the model involving only environment and each cognitive capacity.

Despite the overall similarity of the results based on the two classification procedures, one additional effect of working memory in the noncompensatory environment emerged using the outcome only procedure which does was not identified using the outcome and search classification. To better understand this effect I compared the regression coefficients of the multinomial regression models in which working memory was used as a predictor of strategy use in each environment. Interestingly, while regression coefficients were negative in the compensatory environment (B = -.733; B = -.177; comparison with FR involving TTB and Take Two, respectively) they were positive in the noncompensatory environment (B = .263; B = .406; comparison with FR involving TTB and Take Two, respectively). This reveals that lower scores in working memory were associated with the use of more fugal strategies in the compensatory environment. Conversely, they were positively associated with using a more information-intensive strategy, FR, in the noncompensatory condition. This suggests that working memory served as a marker for different abilities in the two environments: While it signaled limitations in cognitive resources in the compensatory condition, it signaled adaptive use of simpler strategies in the noncompensatory one.

Overall, these results suggest that even though estimated strategy distributions based on an outcome only classification differ to some extent from the preferred outcome and search classification method, the results concerning the relation between cognitive capacity and strategy use do not differ extensively between them.

Table E.2: Effect of Cognitive Capacity Measures on Strategy Use in Study 2 as a Function of Environment based on the Outcome Only Strategy Classification Method

	Compensatory Environment			Noncompensatory Environment		
Predictors	*G*	*DF*	*P*	*G*	*DF*	*P*
WM	6.284	2	.043	9.735	2	.008
STM	12.480	2	.002	.319	2	.853
SPEED	2.211	2	.331	.904	2	.636
RPI	2.569	2	.277	4.348	2	.114
KNOW	3.413	2	.182	5.872	2	.053
REASON	6.626	2	.036	.991	2	.609

WM = Working Memory; STM = Short-term memory; RPI = Resistance to Proactive Interference; KNOW = Knowledge; REASON = Reasoning.

Appendix F

Results of Multinomial Logistic Regression Analyses Based on the Outcome Only Strategy Classification Method for Study 3

The results concerning the relation between cognitive capacity and strategy use in older adults were also investigated using the outcome only classification procedure. The outcome only classification method provided slightly different results compared to an outcome and search procedure. In the compensatory condition, 8 TTB users (19.5 %) were identified, 5 participants (12.2 %) were identified as using Take Two, 22 (53.7 %) as FR, and 6 (14.6 %) were left unclassified. In the noncompensatory condition, 22 (52.4 %) TTB users were identified, 10 participants (23.8 %) were classified as Take Two, 9 as FR (21.4 %), and 1 (2.4 %) being left unclassified. Thus, the outcome only classification identifies a larger proportion of participants relying on FR in the compensatory condition and a larger proportion of TTB users in the noncompensatory condition in comparison with the outcome and search classification.

As was previously done using the outcome and search classification results, I conducted multinomial logistic regressions to assess the predictive value of environment, each measure of capacity, and their interaction, on the use of strategies as classified based on the classification using only participants' choices. The results based on the outcome only classification method showed a main effect of reasoning and working memory. Regression coefficients concerning the relation between the working memory and reasoning factors and the use of frugal strategies were negative, suggesting that lower scores in these measures were associated with the use of more fugal strategies.

Summing up, the results differ somewhat when different classification procedures are used. Namely, an effect of working memory which goes undetected using the outcome and search classification emerges when an outcome only classification is considered. Recall, however, that such an effect of working memory had also been detected at the level of information search when the outcome and search classification was used, with those individuals with larger working memory capacities showing more information intensive strategies. Hence, the two classification procedures converge in showing effects of working memory and reasoning regardless of environment.

Table F.1: Goodness of Fit of a Series of Multinomial Logistic Regression Models with Strategy Classification as the Dependent Variable

		G	*P*	Δ*G*	*P*
Step 1: Environment by itself		13.64	.001		
Step 2: Environment + Capacity	WM	21.94	<.001	8.30	.016
	STM	14.09	.007	0.45	.800
	SPEED	18.74	<.001	5.09	.078
	RPI	13.89	.008	0.25	.882
	KNOW	17.03	.002	3.38	.184
	REASON	27.02	<.001	13.37	.001
Step 3: Environment + Capacity + Environment*Capacity	WM	26.68	<.001	4.74	.093
	STM	14.52	.024	.44	.805
	SPEED	19.46	.003	.73	.695
	RPI	14.41	.025	.51	.773
	KNOW	17.39	.008	.37	.832
	REASON	28.75	<.001	1.73	.421

WM = Working Memory; STM = Short-term memory; RPI = Resistance to Proactive Interference; KNOW = Knowledge; REASON = Reasoning. In Step 2, Δ*G* represents the difference between *G* of the model with environment and cognitive capacity as predictors and that of the model with only environment as predictor. In Step 3, Δ*G* represents the difference between *G* of the model with environment, each capacity, and their interaction as predictors and that of the model involving only environment and each cognitive capacity.

Appendix G

Results of Multinomial Logistic Regression Analyses Based on the Outcome Only Strategy Classification Method for Collapsed Data of Studies 2 and 3

To allow a comparison between classification procedures I performed the same set of analysis concerning the outcome and search classification method using the alternative outcome only classification method. The results for this analysis are presented in Table G.1.

Table G.1: Results of Multinomial Logistic Regression Analyses Involving Environment, Age, and Measures of Cognitive Capacity as Predictors

		G	*P*	Δ*G*	*P*
Step 1: Environment by itself		50.524	.001		
Step 2: Environment + Age		56.944	<.001	6.420	.040
Step 3: Environment + Capacity	WM	58.650	<.001	8.126	.017
	STM	51.401	<.001	.877	.645
	SPEED	58.974	<.001	8.450	.015
	RPI	52.321	<.001	1.797	.407
	KNOW	51.051	<.001	.527	.768
	REASON	64.065	<.001	13.541	.001
Step 4: Environment + Capacity + Environment*Capacity	WM	78.243	<.001	19.593	<.001
	STM	52.717	<.001	1.316	.518
	SPEED	66.330	<.001	7.356	.025
	RPI	52.475	<.001	.154	.926
	KNOW	52.124	<.001	1.073	.585
	REASON	76.641	<.001	12.575	.002
Step 5: Environment + Capacity + Environment*Capacity + Age	WM	80.481	<.001	2.238	.327
	STM	58.870	<.001	6.153	.046
	SPEED	67.310	<.001	.980	.613
	RPI	58.596	<.001	6.121	.047
	KNOW	57.877	<.001	5.754	.056
	REASON	76.749	<.001	.108	.947

WM = Working Memory; STM = Short-term memory; RPI = Resistance to Proactive Interference; KNOW = Knowledge; REASON = Reasoning. In Step 2, Δ*G* represents the difference between *G* of the model with environment and age as predictors and that of the model with only environment. In Step 3, Δ*G* represents the difference between *G* of the model with environment and each capacity as predictors and that of the model involving only environment. In Step 4, Δ*G* represents the difference between *G* of the model with environment, each capacity, and their interaction as predictors and that of the model involving both environment and respective cognitive measure. Finally, in Step 5, Δ*G* represents the difference between *G* of the model with environment, each capacity, their interaction, and age as predictors and that of the model involving the same predictors but age.

Overall, the results based on the two classification procedures converge in showing both an effect of environment and of age on strategy use. However, they differ slightly when the different cognitive measures are concerned. The analysis based on the outcome only classification shows interaction effects between cognitive capacity and environment, suggesting that working memory, speed, and reasoning, play a more relevant role in one environment. Further analysis revealed that this was the case because effects of working memory and reasoning were particularly evident in the compensatory environment. More interestingly, concerning the added predictive power of age over the cognitive capacity variables, both procedures indicate that age does not add explanatory power to models including speed, reasoning, and working memory. In short, age-related differences in strategy use seem to be captured by individual differences in reasoning, speed, and, at least partly, working memory, regardless of the classification method used.

German Summary

Das Hauptziel der vorliegenden Arbeit war es, den Einfluss kognitiven Alterns auf die Auswahl und Anwendung von Entscheidungsstrategien zu verstehen. Zwei Fragen standen dabei im Vordergrund: 1) Die Veränderung der Fähigkeit, Entscheidungsstrategien angepasst auf die Struktur der Umwelt auszuwählen, die mit der Abnahme kognitiver Kapazität im Alter einhergeht; 2) zu untersuchen, wie sich die Fähigkeit, Entscheidungsstrategien effektiv anzuwenden, zwischen jungen und älteren Erwachsenen unterscheidet. Welche Antworten haben wir auf diese Fragen gefunden?

Junge und ältere Erwachsene wählen Entscheidungsstrategien adaptiv aus

In den Studien 1 und 2 wurde die Adaptivität der Strategieauswahl bei jüngeren Erwachsenen untersucht, in Studie 3 hingegen bei einer älteren Stichprobe. In allen drei Experimenten wurde Teilnehmenden eine von zwei Umweltstrukturen präsentiert, in denen entweder die Anwendung von kompensatorischen oder nicht-kompensatorischen Entscheidungsstrategien günstiger war. Das Ziel der Teilnehmenden in allen drei Studien war es, zu entscheiden, welcher von zwei Diamanten der wertvollere war, basierend auf einer Reihe von „Cues“ (hier: Prädiktoren für den Wert des Diamanten). Pro Diamant gab es bis zu acht Cues. Zusätzlich wurde die Rolle, die kognitive Kapazität für die Auswahl von Strategien spielt, mit korrelativen Methoden untersucht.

Die Ergebnisse der drei Untersuchungen zeigen, dass Menschen ihre Entscheidungsstrategien angepasst an die Umweltstruktur auswählten, und unterstützen somit die Annahme einer adaptiven Werkzeugkiste. Insgesamt wies das Suchverhaltenden der Teilnehmenden darauf hin, dass sie in kompensatorischen Umwelten (in denen alle Cues den gleichen Vorhersagewert für das Zielkriterium „wertvoll“ hatten) informationsintensivere Suchstrategien benutzten als in nicht-kompensatorischen Umweltstrukturen (in denen alle Cues unterschiedliche Vorhersagewerte für das Zielkriterium darstellen). Ähnliches gilt auch für die Strategiebenutzung: Einfachere Strategien wurden öfter in der dafür angemessenen, nicht-kompensatorischen Umwelt eingesetzt, wohingegen die Mehrheit der Teilnehmenden informationsintensivere Strategien in den kompensatorischen Umwelten anwendete. Da dieses

Muster in allen drei Experimenten auftrat, unterstützen diese Befunde die Annahme, dass beide, sowohl jüngere als auch ältere Erwachsene Entscheidungsstrategien adaptiv, d.h. angepasst an die jeweilige Struktur der Umwelt, auswählen und können.

Ältere Erwachsene benutzen einfachere Entscheidungsstrategien als jüngere Erwachsene

Bezogen auf Altersunterschiede in Informationssuche und Strategieanwendung konnte gezeigt werden, dass ältere Erwachsene mehr Zeit gebraucht haben, um sich zu entscheiden, und sich weniger Information angesehen haben, als jüngere. Ferner zeigen sich Unterschiede in der Verteilung der angewendeten Strategien zwischen jüngeren und älteren Erwachsenen, wobei ältere Erwachsene im Vergleich zu jüngeren häufiger einfache, informationssparsame Strategien benutzten.

Individuelle Unterschiede in der Kapazität des Arbeitsgedächtnisses, Verarbeitungsgeschwindigkeit und fluide Intelligenz klärten einen Großteil der altersbezogenen Varianz auf. Das ist ein Hinweis darauf, dass ältere Erwachsene vor allem deshalb einfachere Strategien benutzt haben, weil ihre kognitiv mechanischen Fähigkeiten nachlassen. Gleichwohl ist anzumerken, dass sich ältere Erwachsene in ihrer Tendenz, einfache Entscheidungsstrategien zu benutzen, in einer kompensatorischen Umwelt (die informationsintensive Strategien begünstigt) nur wenig von jüngeren Erwachsenen unterscheiden. Im Gegensatz dazu neigen ältere Erwachsene häufiger dazu, einfachere Strategien in nicht-kompensatorischen Umwelten anzuwenden, in Umwelten also, die den Gebrauch einfacher Strategien belohnen. Diese Ergebnisse deuten darauf hin, dass ältere Erwachsene Entscheidungsstrategien nicht nur adaptiv, also angepasst an die Umweltstruktur, auswählen, sondern auch, unter bestimmten Bedingungen, jüngere Erwachsene übertreffen können.

Trotz der insgesamt an die Umwelt angepasste Strategieauswahl der älteren Erwachsenen waren ihre Entscheidungen, welcher Diamant der wertvollere ist, im Durchschnitt seltener richtig als die der jungen Erwachsenen. In Kapitel 3 wird untersucht ob Altersunterschiede in der Strategieanwendung diese Diskrepanz erklären können.

Ältere Erwachsene wenden Entscheidungsstrategien weniger effektiv an als junge Erwachsene

In Kapitel 3 wird ein neuro-computationaler Ansatz präsentiert um die Auswirkungen der altersbedingten Abnahme kognitiver Kapazitäten auf die Anwendung von

Entscheidungsstrategien vorherzusagen. Dieser Ansatz verbindet die Annahme, dass sich Menschen beim Entscheiden aus der adaptiven Werkzeugkiste bedienen (Gigerenzer et al., 1999) mit formaler konnektionistischer Modellierung des Alterns (Li et al., 2000, 2001). Dieser Herangehensweise liegt die Annahme zugrunde, dass altersbezogene Veränderungen neuromodularer Prozesse Kognition auf der Ebene ihrer elementaren Informationsverarbeitungseinheiten wie Arbeitsgedächtnis und Verarbeitungsgeschwindigkeit beeinflussen. Diese altersbezogenen Veränderungen wiederum führen zu Unterschieden auf Verhaltensebene, wie dem effektiven Einsatz von Entscheidungsstrategien.

In Studie 4 wurden drei Vorhersagen des neuro-computationalen Ansatzes empirisch überprüft. Es wurde erwartet, dass 1) im Durchschnitt ein Leistungsunterschied zwischen jüngeren und älteren Erwachsenen bei der Anwendung von Entscheidungsstrategien besteht – ältere Erwachsene sollten insgesamt mehr Anwendungsfehler machen als jüngere; 2) ein Interaktionseffekt zwischen Alter und Schwierigkeit der Entscheidungsstrategien auftritt, wobei die Leistung älterer Erwachsener bei der Anwendung kognitiv anspruchsvollerer Strategien stärker abnehmen sollte als die jüngerer Erwachsener; 3) die intra-individuellen Schwankungen in der Leistung mit dem Alter zunehmen. Im Experiment wurden jüngere und ältere Erwachsene getestet, die zuvor trainiert worden waren informationssparsame und informationsintensive Strategien anzuwenden. Es wurde ausgewertet, wie exakt die beiden Altersgruppen die beiden Entscheidungsmechanismen benutzen konnten. Die Ergebnisse weisen darauf hin, dass ältere Erwachsene häufiger eine Option wählten, die nicht von einer der beiden Strategien vorgeschrieben worden war, und dass ihre Leistung zwischen vergleichbaren Aufgabengruppen stärker schwankte als die jüngerer Erwachsener. Dennoch wurde kein Interaktionseffekt zwischen Alter und Schwierigkeit der Strategie gefunden. Diese Befunde könnten als Hinweis darauf interpretiert werden, dass ältere Erwachsene eine vereinfachte, kognitiv weniger anspruchsvolle Version der informationsintensiven Entscheidungsstrategien anwendeten.

Insgesamt deuten die Ergebnisse darauf hin, dass eine altersbezogene Abnahme kognitiver Kapazität Auswirkungen auf die Effektivität, mit der Strategien gebraucht werden, hat, wobei ältere Erwachsene davon stärker betroffen sind als jüngere. Nichtsdestotrotz, scheinen die Altersunterschiede in der Leistung keinen dramatischen Nachteil der älteren gegenüber den jüngeren darzustellen, was bedeuten könnte, dass die Fähigkeit zu Entscheiden bis ins hohe Alter relativ gut erhalten bleibt. Dass ältere Erwachsene informationsintensive Strategien so anpassen zu können scheinen, dass sie kognitiv weniger anspruchsvoll sind, impliziert dass ihr Entscheidungsverhalten im Kern adaptiv ist.

Scheren haben zwei Klingen: Anpassen an individuelle Eigenschaften und die Umwelt

Der Ansatz der „Selektiven Optimierung durch Kompensation“ (SOK; Baltes & Baltes, 1990) betont die Notwendigkeit, Verhalten an die Veränderungen der persönlichen Ressourcen über die Lebensspanne anzupassen. Andererseits, basierend auf der Annahme einer adaptiven Werkzeugkiste (Gigerenzer et al., 1999), passen Individuen ihr Verhalten der Struktur ihrer Umwelt an. Die hier vorliegende Arbeit integriert beide Ansätze, in dem sie zeigt, dass Personen 1) Entscheidungsstrategien benutzen, die ihren kognitiven Fähigkeiten entsprechen, zum Beispiel Strategien, die mit der eigenen Merkfähigkeit über die Lebensspanne kompatibel sind und 2) ihre Strategien an unterschiedliche Aufgabeneigenschaften, wie die statistische Struktur von Umwelten, anpassen.

Die hier vorliegende Arbeit reflektiert Simons (1957) Vision von menschlichem Geist und Umwelt als zwei Scherenklingen. Sie unterstreicht die Adaptivität menschlichen Verhaltens, die ständig ein Gleichgewicht zwischen individuellen Ressourcen und Eigenschaften der Umwelt schneidet.

Declaration

I hereby declare that this thesis is of my own composition, and that it contains no material previously submitted for the award of any other degree. The work reported in this thesis has been executed by me.

Rui Mata

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