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ERRORES Y SESGOS PSICOLÓGICOS EN LA DETECCIÓN Y ATRIBUCIÓN DE CAUSALIDAD

PSYCHOLOGICAL ERROS AND BIASES IN THE DETECTION AND ATTRIBUTION OF CAUSALITY

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INTRODUCCIÓN (EN CASTELLANO)

Introducción

Cuando las personas toman decisiones, es imposible que consideren o procesen todas las alternativas disponibles de su entorno. Por ejemplo, al comprar un ordenador portátil, nadie considera todos los modelos que existen en el mercado y todas sus características técnicas, sino que seleccionan algunas opciones, por ejemplo en función del precio y la calidad, para decidir cuál comprar (Fasolo, McClelland, & Todd, 2007; Reisen, Hoffrage, & Mast, 2008). Así se logra que la mayoría de las decisiones sean rápidas, porque no implican muchos cálculos, y frugales, ya que la búsqueda sólo se focaliza en ***algunas*** de las claves disponibles en el medio ambiente (Gigerenzer, 2008).

La investigación previa ha demostrado que las personas—en particular en situaciones en las que no son capaces de procesar toda la información disponible en el medio ambiente (Kahnemann, Slovic, & Tversky, 1979; Simon, 1990)—aplican modelos mentales sobre las relaciones entre la causa y el efecto para determinar las claves importantes (Kahnemann & Tversky, 1974; Sloman & Hagmayer, 2006; Waldmann, Hagmayer, & Blaisdell, 2006). Los consumidores, por ejemplo, a menudo creen que la mayor calidad de un producto se asocia con altos costes en la producción, que resultan en precios más altos del producto. Así, un cliente puede creer que el nivel de los precios predice la calidad o exclusividad de un objeto adquirido por los gastos de su producción (Alba, Broniarcyk, Shimp, & Urbany, 1994). El enfoque de esta tesis investiga como el conocimiento sobre la estructura causal del medio ambiente puede ayudar a la gente a llegar a decisiones satisfactorias. Después de una introducción breve para enmarcar el trabajo, se presentan los estudios realizados, unos ya publicado y otros en vías de publicación.

Enfoques teóricos

La literatura sobre la influencia de las creencias causales en la toma de decisiones es muy reciente y sugiere que tales creencias pueden ayudar, pero también pueden obstaculizar el proceso de elección. Algunos autores (Alba et al., 1994; Baumgartner, 1995; Wright & Murphy, 1984) concluyen que las creencias previas ayudan a la evaluación de la covariación y que se puede aumentar la precisión en decisiones, si las creencias causales se utilizan como hipótesis que se comprueban con los datos obtenidos mediante la experiencia directa (Garcia-Retamero, Müller, Catena, & Maldonado, 2009; Meder, Hagmayer, & Waldmann, 2008, 2009; Sloman & Hagmayer, 2006). En concreto, las evaluaciones de las relaciones entre los eventos que son guiados por las creencias causales, como la relación entre precio y calidad, son más precisos que los juicios libres de las creencias sobre estímulos abstractos, especialmente cuando los datos son confusos (Wright & Murphy, 1984). Estos resultados sugieren que las creencias causales pueden tener efectos beneficiosos.

Sin embargo, otros resultados sugieren que las creencias causales pueden también tener efectos perjudiciales. Por ejemplo, parece que las correlaciones objetivas sólo se evalúan correctamente en ausencia de creencias previas o cuando son congruentes con las pruebas empíricas (Alloy & Tabachnik, 1984; Nisbett & Ross, 1980). Se ha demostrado que correlaciones objetivas idénticas se pueden evaluar de manera muy diferente dependiendo de los conocimientos previos sobre la relación entre la causa y un efecto, y más aún si se contradicen la evidencia empírica anterior. Por ejemplo, a los participantes en un estudio realizado por Evans, Clibbens, Cattani, Harris, y Dennis (2003; Evans, Clibbens, & Harris, 2005) se les proporcionó información compatible, incompatible o neutra con sus creencias previas. Los resultados mostraron que sus creencias previas sólo mejoraron los juicios cuando la evidencia empírica era compatible. Una explicación de este resultado puede ser que los participantes sobrevaluaron las creencias antes de evaluar las contingencias reales (Fugelsang & Thopmson, 2003; Klayman, 1995). De esta manera, solo aceptaron información que confirmaba sus creencias previas e ignoraron la información conflictiva.

Diversos enfoques teóricos se han focalizado en la relación entre creencias causales y la información directa de covariación entre claves y consecuencias (véase Ahn & Kahish, 2000; De Houwer & Beckers, 2002; Perales & Catena, 2006; Waldmann & Hagmayer, 2001). En unos casos, se conceptualiza una relación causal desde un enfoque asociativo de aprendizaje (Shanks & Dickinson, 1987; Wassermann, Chatlosh & Neunaber, 1983) o como el resultado del cómputo estadístico (Cheng, 1997) entre la causa y el efecto. Este enfoque implica un proceso bottom-up del aprendizaje. Por el contrario, otro tipo de modelos suponen la existencia de un conocimiento abstracto de la causalidad, que permite las personas evaluar una relación cuando se presenta con los datos de covariación (Ahn, Kahlish, Medin, & Gelman, 1995; Waldmann & Holyoak, 1992).

Modelos más recientes tienen en cuenta ambos enfoques a la hora de explicar el proceso de aprendizaje causal (Maldonado, Catena, Cándido, & Garcia, 1999; véase Fugelsang & Thompson, 2003; Lien & Cheng, 2000, para otros enfoques). Según la propuesta original del modelo de revisión de creencias (Catena, Maldonado, y Cándido (1998; BRM), el aprendizaje de relaciones causales depende de un proceso de revisión de creencias basado en la acción serial de dos mecanismos. En primer lugar, antes de la emisión de un juicio causal, un mecanismo básico de aprendizaje sería el encargado de calcular la contingencia establecida entre dos sucesos (la causa y el efecto) a partir de las frecuencias de cada tipo de ensayo, almacenadas en la memoria de trabajo. Sobre esta información, un segundo mecanismo cognitivo sería el encargado de integrar esta información o nueva evidencia con las creencias previas que el sujeto posee en función de su experiencia previa. En este modelo, las creencias previas sobre la relación de la causalidad no serían un filtro absoluto frente a nuevos datos de covariancia. Por el contrario, representan un ancla-y-ajuste de las creencias o la clasificación de nueva evidencia, similares a un intento anterior de Hogarth y Einhorn (1992).

Por último, un enfoque más reciente que investiga el aprendizaje de las relaciones de causalidad son los modelos basados en redes bayesianas (Griffiths & Tenenbaum, 2005; Waldmann, 2000). Para aplicar está enfoque se necesita información suficiente acerca sobre las estructuras del medio ambiente. Estas redes bayesianas se muestran a través gráficos acíclicos en el cual los nodos representan los variables (tipo de eventos o estados del mundo) y los bordes (flechas) representan las relaciones directas de la causalidad o la dependencia probabilística entre las variables (ver también Waldmann et al., 2006). Un problema con estas redes es la dificultad de cómputo cuando tenemos un numero alto de datos, en cuyo caso, es prácticamente imposible para estas redes bayesianas de identificar la estructura causal subyacente de los mismos.

El proyecto de la tesis

En línea con otros autores (Garcia-Retamero, Diekman, & Wallin, 2007; Meder et al., 2008; Sloman & Hagmayer, 2006; Waldmann, Hagmayer, & Blaisdell, 2006), la hipótesis de este tesis se focaliza en que la gente no procesan todas las claves posibles en su entorno natural sino que utilizan sus conocimientos de la causalidad (es decir, su conocimiento sobre las relaciones causales entre los eventos en el medio ambiente) para concentrarse en un subconjunto pequeño y manejable de las claves pertinentes. Más concretamente, se asume que el conocimiento sobre relaciones causales podría ser uno de los índices más importantes en el aprendizaje de la validez de claves de nuestro medio ambiente cuando tenemos que tomar decisiones y cuando hacemos atribuciones causales en nuestro propio medio ambiente. La validez de una clave se define como la probabilidad de que esté presente en la opción correcta, dado que discrimina entra las alternativas de elección (Gigerenzer, Todd & the ABC research group, 1999).

Para investigar la influencia del conocimiento causal y la experiencia directa (validez de las claves) en la toma de decisiones y juicios causales, todos los experimentos de esta tesis utilizan una tarea de elección forzosa entre pares, en donde las dos alternativas aparecen descritas en función de cuatro claves. Dos de dichas claves siempre tenían una validez alta y las otras dos tenían validez baja, lo que significa que tenían un grado de relación objetiva (covariación) alta o baja, respectivamente. Además, se manipulaba la estructura causal o las creencias causales previas sobre dichas claves para poder analizar la influencia del conocimiento causal previo, más allá de la mera covariación. Finalmente, una aportación importante también de este trabajo es el estudio conjunto de la influencia de las variables previas no sólo en los juicios de causalidad, sino también en la toma de decisiones, dado que la investigación previa ha documentado diferencias entre inferencias causales en función de la posibilidad intervenciones, y no como producto de la mera observación de regularidades en el medio ambiente (Hagmayer & Sloman, Meder et al., 2009). El objetivo final sería el estudio de los factores y el desarrollo de modelos que permitan entender las relaciones entre ambos procesos: toma de decisiones y atribuciones de causalidad en nuestro propio medio ambiente, dado que modelos recientes han extendido los modelos causales a la toma de decisiones en humanos (Sloman & Lagnado, 2006).

En suma, las creencias causales podrían permitir al tomar decisiones o hacer juicios causales, a manejar de forma más adaptativa la cantidad enorme de las claves que aparecen en el medio ambiente y seleccionar sólo aquellas que son potencialmente relevantes. En los artículos de esta tesis se ofrecen predicciones más precisas acerca de cómo el conocimiento causal puede influir en los procesos de la toma de decisiones y juicios causales.

En el ***capítulo 1*** (García-Retamero, Müller, Catena, y Maldonado, 2009), los experimentos se centran en el análisis de la influencia de las creencias causales y la evidencia empírica sobre la toma de decisiones y juicios de causalidad. La hipótesis principal de este trabajo fue que las creencias causales tendrían una mayor influencia sobre los juicios de causalidad que en la toma de decisiones. Además, los autores proponían la hipótesis de que la evidencia empírica se puede integrar más fácilmente en las decisiones y en los juicios causales, cuando se realiza un pre-entrenamiento con claves neutrales para reducir la influencia de la información causal.

El ***capítulo 2*** (Müller, García-Retamero, Cokely, y Maldonado, 2011, en prensa), tuvo como objetivo ampliar la comprensión de la interacción dinámica de las creencias causales, la toma de decisiones y los juicios de causalidad. La hipótesis principal de este estudio fue que los participantes pueden mejorar su evaluación de la evidencia empírica en la toma de decisiones con una mayor experiencia y con la disponibilidad de claves que varían mucho en la validez de su predicción. Además, los autores se focalizaron en desentrañar los factores que pueden explicar la disociación demostrada previamente entre juicios causales y decisiones. Como la investigación previo indica diferencias entre observaciones e intervenciones (Hagmayer & Sloman, Meder et al., 2009), información causal también podría afectar las decisiones de manera diferente a los juicios causales.

En el ***capítulo 3*** (Müller, García-Retamero, Galesic, y Maldonado, enviado a publicación en JEPA) se estudia la influencia de las creencias causales en la toma de las decisiones y los juicios de causalidad en dos diferentes dominios, medico y financiero.

Como la mayoría de la investigación sobre los juicios causales y la toma de decisiones sólo se refieren a un dominio particular, los autores proponen la hipótesis de que las creencias causales serían más fuertes y por tanto tendrían una mayor influencia en las decisiones y los juicios de causalidad en el dominio médico de que el dominio financiero. Dos razones que explicarían esta hipótesis serían, en primer lugar, que las personas perciben una mayor estabilidad y por tanto menor variabilidad de la validez de las claves en el dominio medico que en el dominio financiero. En segundo lugar, en el dominio medico las consecuencias parecen más importantes porque pueden implicar una amenaza para la vida.

En estos experimentos, la tarea de comparación de pares de elección forzosa se enmarca como tarea de diagnóstico médico o financiero. Las claves causales proporcionaban información específica del dominio medico o financiero, para investigar la fuerza de las creencias causales en ambos dominios y la capacidad de integrar la evidencia empírica. Una diferencia fundamental con las series anteriores es que a la mitad del entrenamiento hubo un cambio en la validez objetiva de las claves.[1] De esta forma, ser pretendía analizar aún más la influencia de la experiencia directa en el proceso de toma de decisiones y la posterior atribución de causalidad en función de dicha experiencia.

El ***capítulo 4*** (Müller, García-Retamero, Galesic, Catena, Perales y Maldonado, enviado para su publicación en QUEP) investiga la interacción entre la frecuencia de los juicios y la (in)flexibilidad de las creencias causales en función del dominio. La hipótesis básica era de que la frecuencia de los juicios facilita un ajuste de los juicios causales a la evidencia empírica proporcionada en la tarea de comparación de pares de elección forzosa. Para evaluar el grado de que las creencias causales son sensibles a los

[1] En el Experimento 1 y 2, claves con alta validez cambiaron a validez baja y vice versa. En el experimento 3, todas las claves generativas cambiaron a validez baja después de la primera fase de la tarea de decisiones.

efectos de anclaje-y-ajuste en cada uno de los dos dominios, se manipuló la frecuencia del juicio además de la información causal. Por último, este artículo intenta explicar el proceso de toma de decisiones y el proceso de atribución de causalidad desde un modelo basado en la integración de la fuerza de una creencia causal y la fiabilidad otorgada a la evidencia empírica.

En el ***resumen y conclusión general***, se pretende integrar todos los conocimientos acumulados y los resultados obtenidos en los estudios presentados en esta tesis. Este resumen ofrece una breve descripción de los resultados de los estudios presentados en el capítulo 1, 2, 3 y 4, poniendo de manifiesto las conclusiones más importantes. Además, se propone un marco teórico que pretende explicar cómo se integran tanto la evidencia empírica y la fuerza de las creencias causales tanto en la toma de decisiones, como en el razonamiento causal. Por último, se analizan algunas de las limitaciones del presente trabajo y las posibilidades de investigación futura.

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INTRODUCTION (ENGLISH)

The Influence of Causal Knowledge in Two-Alternative Forced-Choice Tasks[2]

Abstract

Making decisions can be hard, but it can also be facilitated. Simple heuristics are fast and frugal but nevertheless fairly accurate decision rules that people can use to compensate for their limited computational capacity, time, and knowledge when making decisions. These heuristics are effective to the extent that they can exploit the structure of information in the environment in which they operate. They require knowledge about the predictive value of probabilistic cues. However, it is often difficult to keep track of all the available cues in the environment and how they relate to any relevant criterion. We suggest that knowledge about the causal structure of the environment helps decision makers focus on a manageable subset of cues, thus effectively reducing the potential computational complexity inherent in even relatively simple decision-making tasks. Specifically, we claim that causal knowledge can act as a meta-cue for identifying highly valid cues and help to estimate cue-validities. Causal knowledge, however, can also bias people's decisions. We review experimental evidence that tested these hypotheses.

Introduction

When people are faced with a decision, it is often impossible to consider all of the available alternatives and to gather and process all of the information about those alternatives. For instance, to buy a laptop, most people would not consider every model that exists on the market, but winnow down the set of options to inspect closer using features such as price and quality. They might not analyze all features of the remaining

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laptops either, but request only certain cues to decide which one to buy (Fasolo, McClelland, & Todd, 2007; Reisen & Hoffrage, 2008). Such decisions are fast because they do not involve much computation, and they are frugal because they only search for some of the available information in the environment (Gigerenzer, 2008).

Previous research has shown that people—in particular in situations in which they are not able to process all available information in the environment (Kahnemann, Slovic, & Tversky, 1982; Simon, 1990)—often use mental models about cause-effect relations when determining which cues to consider (Kahnemann & Tversky, 1979; Sloman & Hagmayer, 2006; Tversky & Kahnemann, 1974, 1981; Waldmann, Hagmayer, & Blaisdell, 2006). Consumers, for instance, often believe that high product quality is associated with high production costs, resulting in higher prices. Thus, a customer may believe that the price-level predicts the quality, exclusiveness, or abstract value of a purchased object due to its production expenses (Alba, Broniarczyk, Shimp, & Urbany, 1994). In this paper, we posit that such knowledge about the causal structure of the environment can help people to reach satisfying decisions. Specifically, we analyze the impact of causal knowledge in two-alternative forced choice tasks and present, after a theoretical introduction, various findings and insights that are relevant to this topic.

In general, the decision making literature that focuses on the influence of causal beliefs suggests that such beliefs are like a double-edged sword: They can help or hinder. Some authors (e.g., Baumgartner, 1995; Alba et al., 1994; Wright & Murphy, 1984) conclude that prior beliefs boost peoples' covariation assessment and may increase decision accuracy if the causal beliefs are used as hypotheses that are tested on data (Baumgartner, 1995; Garcia-Retamero, 2007; Garcia-Retamero & Hoffrage, 2009; Meder, Hagmayer, & Waldmann, 2008, 2009; Sloman & Hagmayer, 2006).

Specifically, assessments of relationships between events that are guided by causal beliefs, such as the relationship between price and quality, are more accurate than belief-free judgments about abstract stimuli, especially when the data are noisy (Baumgartner, 1995; Wright & Murphy, 1984). These findings suggest that causal beliefs can have beneficial effects.

Other findings, however, suggest that such beliefs can also have detrimental effects. For instance, it seems that objective correlations can only be assessed correctly when relevant prior beliefs are absent or congruent with the empirical evidence (e.g., Billman, Bornstein, & Richards, 1992; Nisbett & Ross, 1980; Alloy & Tabachnik, 1984). Moreover, identical objective correlations can be judged very differently depending on whether prior knowledge about the relationship between a cause and an effect conflicts with empirical evidence or not. For instance, participants in a study by Evans, Clibbens, Cattani, Harris, and Dennis (2003; see also Evans, Clibbens, & Harris, 2005) were provided with information compatible, incompatible, or neutral with their prior beliefs. The results showed that their beliefs only improved judgments when the empirical evidence was compatible. An explanation for this result may be that participants overvalued prior beliefs when assessing actual contingencies (Chapman & Chapman, 1967; Fugelsang & Thompson, 2004; Klayman, 1995). In that way, only information confirming their prior beliefs was taken into account, whereas conflicting information was ignored.

Various theoretical approaches have been used to shed more light on the relation between causal beliefs and covariation information (for overviews, see Ahn & Kalish, 2000; De Houwer & Beckers, 2002; Perales & Catena, 2006; Waldmann & Hagmayer, 2001). Two approaches are particularly worth mentioning. The first conceptualizes a causal relationship as a function of the associative weights (e.g. Shanks & Dickinson, 1987; Wasserman, Elek, Chatlosh, & Baker, 1993) or the statistical relationship (Cheng, 1997) between cues and outcomes acquired during previous training. This approach implies a bottom-up learning process. In contrast, the second approach presumes an abstract knowledge of causality, which allows individuals to assess a relation when presented with covariation data (Ahn, Kalish, Medin, & Gelman, 1995; Waldmann & Holyoak, 1992).

There are also several theoretical attempts that integrate these two approaches – for instance, the belief revision model (BRM; Catena, Maldonado, & Cándido, 1998; Maldonado, Catena, Cándido & Garcia, 1999; see Fugelsang & Thompson, 2003, Lien & Cheng, 2000, for other attempts). In this model, previous knowledge about causation is not an absolute filter of the new covariation data. Instead, it represents an anchor adjusting the beliefs or classifying new evidence, similar to an earlier attempt on belief updating by Hogarth and Einhorn (1992).

Finally, another approach addressing causal relations are causal Bayesian networks (Griffith & Tennenbaum, 2005; Tennenbaum, Griffiths, & Niyogi, 2007; Waldmann, 2000). To apply such networks sufficient information about the environmental structures needs to be provided. These networks are displayed through directed acyclic graphs in which the nodes represent the variables (types of events or states of the world) and the edges (arrows) represent the direct causal relations or probabilistic dependence between those variables (see also see also Waldmann et al., 2006). A problem with causal Bayesian networks is computational intractability: When fed with large scale data sets, including thousands of variables, it is essentially impossible for these networks to identify the causal structure underlying the data.

The fast and frugal heuristics approach and the problem of cue selection

A prominent approach in decision making is the fast and frugal heuristics research program proposed by Gigerenzer and the ABC Research Group (Gigerenzer, 2008; Gigerenzer, Hoffrage, & Goldstein, 2008; Gigerenzer, Todd, & the ABC Research Group, 1999; Todd, Gigerenzer, & the ABC Research Group, in press). One of the fast and frugal heuristics is take-the-best (Gigerenzer & Goldstein, 1996, 1999). This heuristic is designed for two-alternative forced-choice tasks and can be used to infer which of two alternatives has a higher value on a quantitative criterion, such as which of two university professors earns more money. The alternatives are described on several dichotomous cues such as gender or whether the professor is on the faculty of a state or a private university. These cues allow making probabilistic inferences about the criterion. Similar to other fast and frugal heuristics of this research program, take-the-best is constructed from building blocks (i.e., precise steps of information gathering and processing involved in making a decision). Specifically, this heuristic has a search rule, which defines the order of information search (take-the-best looks up cues in the order of their validity, i.e., the probability that a cue will point to the correct decision given that it discriminates between the alternatives); a stopping rule, which specifies when to stop the search (take-the-best stops after the first discriminating cue); and a decision rule, which specifies how to use the gathered information when it comes to making a decision (take-the-best chooses the alternative favored by the first discriminating cue).

The take-the-best heuristic has been subjected to empirical tests in a number of studies (e.g., Bergert & Nosofsky, 2007; Bröder, 2000, 2003; Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003a; Newell, Rakow, Weston, & Shanks, 2004; Newell & Shanks, 2003; Rieskamp & Hoffrage, 2008). There is accumulating experimental evidence for the use of this heuristic, especially under high information acquisition costs (e.g., Bröder & Gaissmaier, 2007; Garcia-Retamero, Hoffrage, & Dieckmann, 2007), time pressure (Rieskamp & Hoffrage, 1999, 2008), and when participants have previous knowledge and experience in the domain (Garcia-Retamero & Dhami, 2009a, 2009b). Newell, Weston, and Shanks (2003) tested to what extent participants' behavior was consistent with take-the-best's building blocks. Their results revealed that only 75% of participants followed take-the-best's search rule (cues hierarchy established by validity) and its stopping and decision rules were obeyed in 80% and 89% of the trials, respectively (see also Newell & Shanks, 2003).

However, these experimental results on the use of take-the-best need to be qualified (see also Meder, Gerstenberg, Hagmayer, & Waldmann, 2010). In many of these studies, participants were encouraged to use cues in the order of their validity by being informed about cue validities or the validity order (e.g., Bröder, 2000, 2003; Bröder & Schiffer, 2003b; Newell et al., 2003). When search by validity was tested against alternative search orders, validity was not the search criterion that predicted participants' searches best (Newell et al., 2004). Instead, it seemed to be the case that participants used simple rules for ordering cues based on trial-by-trial learning (Dieckmann & Todd, 2004; Todd & Dieckmann, 2005, in press). The cue orderings established through such rules do not necessarily converge toward the cue ordering established by validity. Participants, therefore, might have had difficulties computing cue validities and then searching for cues accordingly, even though relatively few cues (i.e., four to six) were available in those experiments.

The problem of searching for good cues seems to be even more severe when one considers that in most situations there are myriad potential cues that could be used to make a decision, and it is practically impossible to keep track of them all and to compute their validities for any potentially relevant criterion (Juslin & Persson, 2002).

Cue selection is further complicated if potential combinations of cues (i.e., compound cues) are taken into account (Bergert & Nosofsky, 2007). Yet sometimes an accurate decision requires people to do so (Garcia-Retamero, Hoffrage, Dieckmann, & Ramos, 2007). For example, some medications might have side effects, such as nausea, if ingested together with alcohol, whereas neither the drug nor the alcohol would cause any problems if ingested alone (of course, this would also depend on the amount of alcohol or drugs that is consumed). As a consequence, a strategy that processes all possible cues would be computationally too demanding. It is also not plausible to assume that the brain comes “prewired” to represent each of the possible cues to predict a criterion.

In line with other authors (Meder et al., 2010; Sloman & Hagmayer, 2006; Waldmann et al., 2006), we hypothesize that people do not process all possible cues in their natural environments but rather use their causal knowledge—i.e., their knowledge about causal relationships between events in the environment—to focus on a small and manageable subset of relevant cues. We further expect that causal knowledge might also aid learning of cue validities. In sum, causal knowledge might allow decision makers to deal adaptively with the huge number of cues that appear in the environment and to select only those that are potentially relevant. In the remainder of this paper, we offer more precise predictions about how causal knowledge can influence decision-making processes and review experimental tests of these predictions.

The adaptive value of knowledge about the causal texture of the environment

When it comes to decision-making, we hypothesize that causal knowledge is advantageous for two reasons. First, causal knowledge might act as a meta-cue that enables people to identify or to determine valid cues in the environment. Second, causal knowledge might help to specifically focus on certain cue-criterion correlations, which, in turn, facilitates learning of cue validities. In the following, we elaborate on these advantages in more detail.

Considering the first advantage, we estimate that cues that are causally linked to the criterion tend to be more valid than cues lacking such a connection to the criterion (Garcia-Retamero, Wallin, & Dieckmann, 2007; see also Ahn & Kalish, 2000; Sloman & Hagmayer, 2006; Wallin & Gärdenfors, 2000; Waldmann et al., 2006). For instance, lung cancer (here, an effect) is more likely to be predicted from a well-established smoking habit (i.e., a cause) than from yellowed fingers (i.e., a second effect of the common cause; see Boyle, 1997). Furthermore, correlations between events that are causally linked are likely to be more robust across environments (i.e., less sensitive to contextual changes) than those without such a connection (Pearl, 2000; Reichenbach, 1956). Following our example, the correlation between smoking and lung cancer would be more robust across different series of patients than the correlation between lung cancer and yellowed fingers would be. We could expect this to be the case even if we control for other alternative causes that could bring about yellowed fingers (e.g., being a painter) that might reduce their predictability for lung cancer. We hypothesize that this asymmetry between causal and non-causal cues that holds in the physical world would be reflected in human cognitive processes. We therefore expect decision makers to use their causal knowledge as a meta-cue for selecting highly valid and robust cues in the environment.

Secondly, causal knowledge might reduce the number of cue–criterion correlations to keep track of when computing cue validities (Garcia-Retamero et al., 2007). This hypothesis is supported by research using multiple cue probability learning. In this paradigm, participants have to predict the criterion of a given object from multiple cues that are probabilistically related to this criterion. Previous empirical studies that use this paradigm (see Kruschke & Johansen, 1999, for a review) suggest that cues interfere with each other when participants try to learn their validities concurrently. For instance, the presentation of irrelevant cues in such a task reduces the utilization of valid cues and, consequently, the accuracy of people's judgments (Castellan, 1973; Edgell & Hennessey, 1980). An explanation for this finding, which can be observed even after a large number of learning trials, suggests that the irrelevant cues made it harder for participants to identify and focus on the valid cues. In contrast, when participants have the opportunity to learn cue–criterion relationships sequentially (i.e., for one cue after another), their judgments correspond more closely to the ecological correlations (Brehmer, 1973). Based on these results, we suggest that in multiple-cue settings people with access to causal knowledge might be able to focus on certain (causal) cues, which in turn might facilitate cue validity learning.

Note, however, that causal knowledge about the cues in the environment also has to be learned (Waldmann et al., 2006). Our argument, therefore, only holds if the acquisition of causal knowledge is simpler than cue validity learning. We think that this is in fact the case. Consider, for instance, learning of causal Bayesian nets. Such learning is certainly not necessarily simple, but it could be simplified if prior specific or abstract domain knowledge about the structure of the environment (e.g., causal directionality) constrains the number of potential causal relations that need to be considered (see Tenenbaum et al., 2007; Waldmann, 1996; Waldmann & Martignon, 1998).[3]

[3] Along these lines, research in the field of artificial intelligence has recently proposed a number of algorithms capable of easily inferring causal relations from covariation patterns (e.g., the TETRAD II program; Spirtes, Glymour, & Scheines, 1993, 2000). These algorithms use causal models to generate a certain pattern of statistical dependencies and then search for certain clues that reveal fragments of the underlying structure. These fragments are pieced together to form a coherent causal model.

Similarly to other scholars (Meder et al., 2008, 2009; Sloman & Hagmayer, 2006), we hypothesize that causal knowledge might allow decision makers to constrain the countless number of cues that appear in a particular environment to a subset of cues that are more likely to have a high predictive value. In the following sections, we review some experiments that tested whether causal knowledge helps people to select a subset of reliable cues and whether it aids learning of cue validities.

Causal knowledge as an aid in cue selection

Recent findings on causal knowledge in decision making stress the difference between observations and interventions (Lagnado, Waldmann, Hagmayer, & Sloman, 2007; Waldmann et al., 2006). Garcia-Retamero, Wallin, and Dieckmann (2007) offer another attempt to examine the impact of causal information about cue-criterion relationships on decision-making processes. Specifically, these authors analyzed whether causal knowledge about the cues in the environment had an effect on the selection of a subset of cues that were used to make decisions and whether it facilitates the computation of cue validities.

Based on the assumption that causal knowledge helps to identify highly valid cues in the environment, Garcia- Retamero, Wallin, and Dieckmann (2007) hypothesized that participants would look up cues that were causally connected to the criterion (in short, causal cues) earlier than non-causal cues, even when these cues had the same validity. Participants were also expected to rely on causal cues to a greater extent than on non-causal cues in their decisions, and to be more confident and faster in their decisions when causal cues were available than when no causal cues were available. On the other hand, given that causal knowledge reduces the number of cue–criterion relationships to keep track of to compute validity, those authors hypothesized that participants would be more exact in their validity estimates for causal than for non-causal cues and, consequently, would also be more accurate in their inferences.

Two experiments test these hypotheses: The first tested the prediction that causal cues are preferred over non-causal cues, the second tested whether this was still the case if participants were allowed to learn cue validities after having been informed which cues were causally linked to the criterion. The experiments were computer-based and used two alternative forced-choice tasks (see Figure 1). On each trial, participants were presented with two alternatives (i.e., two species of insects) and had to decide which would show a higher criterion value (i.e., which would do more damage to a crop). To make this decision, they could look up information on up to four cues (i.e., properties of the insects, such as the presence or absence of a particular metabolic factor), represented by small boxes on the screen that could be clicked to retrieve information (see also Bröder, 2000, 2003; Garcia-Retamero et al., 2007; Rieskamp & Hoffrage, 2008, for similar experimental procedures).

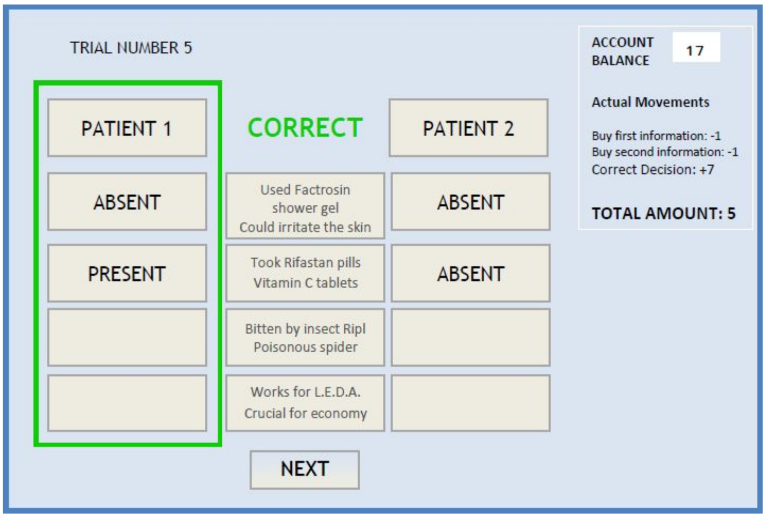

Figure 1: Screenshot of the experimental interface.
On this trial, the participant began by accessing whether the insects had a specific metabolic factor. This cue did not discriminate between the two insects—none of them showed the metabolic factor. The participant then accessed whether the insects had a long larval phase. This cue showed a positive value for insect 1 and a negative value for insect 2. The participant responded that insect 1 was more likely to do greater crop damage, which was a correct response. The participant earned 5 points (7 – 1 – 1) in total on this trial.

Two of these cues had a high validity (.85) and the other two had a low validity (.65; see Table 1). Whether a specific cue had a high or a low validity was counterbalanced across participants. All four cues had a discrimination rate of .56.2[4] Causal knowledge was manipulated between-subjects. In the causal group, participants were told that two of the cues were causally related to the criterion (e.g., "the metabolic factor makes the insects hungry and aggressive"). These formulations suggested an underlying causal mechanism that went beyond the possible covariation between the cue and the criterion. The remaining two cues were neutral and participants were informed that they were not causally linked to the criterion (e.g., "the metabolic factor leads to green and blue coloration of the insects' body").

Table 1. Design of Experiments 1 and 2

		Experimental Group		Control Group
		Information about the cue-criterion relation		
		Causal	**Neutral**	**Neutral**
Cue validity	**High**	Cue 1	Cue 2	Cue 1, Cue 2
	Low	Cue 3	Cue 4	Cue 3, Cue 4

Note. In the experimental group, cue validity and information about the cue-criterion relation (causal knowledge) was manipulated within-participants. Which cue was assigned to which of the resulting four conditions was counterbalanced across participants. In the control group, no causal information was given, only cue validity was manipulated.

Which cues were causally linked to the criterion and which were neutral was counterbalanced across participants. Moreover, the two experimental factors, cue validity and causal knowledge, were completely crossed within participants so that for each participant, one of the causal cues had a high validity and the other had a low validity, and one of the neutral cues had a high validity and the second one had a low validity (Table 1). In the control group, information about all four cues was neutral. A

[4] The discrimination rate of a cue is the proportion of paired comparisons in which the two decision alternatives have different value for that cue (Gigerenzer & Goldstein, 1996).

pretest confirmed that the causal cues, but not the neutral cues, were indeed perceived as having a strong causal effect on the criterion.

In the first experiment, participants went through a decision phase in which the absence or presence of the cues (for each insect) was not automatically displayed; instead they had to actively access information for one cue after another. When a cue was accessed (at the cost of 1 Eurocent) the cue values (presence/absence) of both alternatives (insects) were shown. After having accessed at least one cue, participants were allowed to stop their cue search and decide for one of the alternatives (insects). Subsequently, feedback was provided whether their decision was correct (if so, they earned 7 Eurocents). At the end of the experiment, participants estimated the validity of each cue. In the second experiment, participants entered the decision phase only after they had gone through a learning phase in which the values of the four cues were provided automatically and in which participants could learn the validities of these cues.

In line with the authors' hypothesis, participants in Experiment 1 preferred to start searching for causal cues, regardless of the cue validity. Altogether, that is, across all the cues they accessed, they also favored the causal cues more often than the neutral cues. Moreover, they were faster and more confident in their decisions when they could rely on causal cues as compared to trials in which only neutral cues discriminated. Finally, participants were better in estimating the validities of the causal cues than of the neutral cues. Note that participants showed a preference for causal over neutral cues although they could learn via feedback which cues were reliable predictors (i.e., had high validity) of the criterion throughout the decision-making phase.

When participants in Experiment 2 had the opportunity to learn about cue validities before the actual decision-making phase, their search processes were influenced by both causal information and validity. More precisely, participants who had access to causal information (the causal group) preferred to search for the causal high-validity cue over the rest of the cues. Furthermore, these participants became more accurate in their decisions and were also more accurate, across all cues, when estimating cue validities. Overall, the higher frugality and accuracy in the causal group led to a higher final payoff than in the control group.

In sum, the experimental results suggest that participants may use information about which cues are causally related with the criterion to zoom in on a manageable subset of cues and to learn their validities more accurately.

The flexibility of causal beliefs: when previous beliefs conflict with empirical evidence

Based on these results, Garcia-Retamero, Müller, Catena, and Maldonado (2009) went one step further and investigated whether the relative impact of causal beliefs and empirical evidence on decision making can be altered by previous experience. Two experiments were set up as a series of two-alternative forced-choice tasks, framed as medical diagnostic tasks. In each trial, participants were asked to decide which of two patients would show a higher degree of allergic dermatitis. To make each decision, four cues were available that described both patients and participants had to search for this information.

The design and the procedure were similar to the experiments mentioned above: To analyze the influence of causal beliefs, participants were instructed that two of the four presented cues were causally linked to the criterion ("causal cues"). Instructions for the remaining two cues did not provide any causal link to the criterion ("neutral cues"). For instance, a cue containing the information that the patients ingested a certain prescription drug (Rifastan pills) could either be causal ("an antibiotic, which could lead to skin swelling") or neutral ("vitamin C tablets, which are crucial for sight"). A pretest confirmed that causal—but not neutral—cues were perceived to have a strong causal power.

The impact of the empirical evidence was examined by manipulating cue validities within-subjects: Two of the four available cues (one causal and one neutral cue) had high validity (i.e., 0.9 in both experiments); the remaining two cues had low validity (i.e., 0.6 in Experiment 1 and 0.1 in Experiment 2; see also Table 2). All four cues had a discrimination rate of .59 and inter-cue correlations were close to zero.[2]

At the beginning of the experiment, some of the participants underwent pre-training with either causal (pre-causal group) or neutral cues (pre-neutral group; see also Table 2).

Table 2. Design of Experiments1 and 2

Experimental Groups	Instructions	Cues Pre-Training	Instructions	Cues Decision Task
Control Causal Group		---	Causal	Causal high validity Causal low validity Neutral high validity Neutral low validity
Pre-Causal Group	Causal	Causal high validity Causal low validity	Causal	Causal high validity Causal low validity Neutral high validity Neutral low validity
Pre-Neutral Group	Neutral	Neutral high validity Neutral low validity	Causal	Causal high validity Causal low validity Neutral high validity Neutral low validity

During the pre-training, the cue values for each patient were displayed automatically — no cue search was required. Both groups were asked to make 60 decisions and outcome feedback was provided. Members of the causal control group did not receive any pre-training. Thereafter, both groups of participants completed a decision phase similar to that described above.

The results of the experiments by Garcia-Retamero, Müller, Catena, and Maldonado (2009) revealed that the impact of causal beliefs and empirical evidence depends on both the experienced pre-training and the cue validity. While participants without any pre-training relied mainly on their causal beliefs—favoring causal over neutral cues—pre-training with causal cues led to a clear preference for the causal high-validity cues. Increasing the difference between the validities of the cues reduced the influence of the causal beliefs in both groups: This manipulation led first to decisions in favor of the causal high-validity cue, and secondly to decisions in favor of the neutral high-validity cue. Finally, when participants received pre-training with neutral cues (i.e., not causally linked to the criterion), their decisions were primarily based on the high-validity cues, regardless of their induced causal or neutral relation to the outcome. These results could be observed in both experiments and suggest—in line with other research (Lagnado et al., 2007; Meder et al., 2008, 2009; Waldmann et al., 2006)—that it is necessary to consider the joint effects of causal beliefs and empirical evidence to explain the flexibility involved in human inferences.

We can conclude from these findings that participants rely on their causal beliefs by default—especially when the validities of the cues that are supposed to be causally related to a criterion are high. In this case, participants did not take the cue validities of neutral cues into account. However, when participants received pre-training with neutral cues (i.e., not causally linked to the criterion), they became more sensitive to the validity information (i.e., they were able to discriminate high-validity from low-validity cues) and additional information about causal mechanisms failed to have further relevance. The neutral pre-training could have evoked participants' preference for the cue validities independent of causal information. Interestingly, when high validity cues differed substantially from low validity cues (up to the point where some of the cues were almost not related to the criterion), decisions were mainly based on the high-validity cues, especially the cue that was causally linked to the criterion. Taken together, for participants who received pre-training with neutral cues or cues that provided conflicting information with previous causal beliefs, responses were mainly influenced by cue validities and—to a lesser extent—by causal beliefs.

General conclusions

The reviewed research confirms what we stated in the introduction: causal knowledge about the causal structure of the environment is like a double-edged sword—it can help or hinder. Causal knowledge helped people to focus on a small and manageable subset of cues. It strongly influenced which cues were looked up, in which order they were looked up, and which of them were used to make decisions. Causal knowledge also facilitated cue validity learning—not an easy task, as Juslin and Persson (2002) pointed out. Taken together, these findings suggest that causal knowledge can effectively reduce the computational complexity inherent in decision making tasks. At the same time, it should be pointed out that participants who were equipped with causal knowledge and who did not have an opportunity to learn the cue's validities before making decisions preferred causal, low-validity cues over neutral, high-validity cues, even though they received feedback after each decision.

Seen through the lens of the fast and frugal heuristics framework, causal knowledge helps people to select valid cues in the environment, which might be placed in a high position in the cue ordering, that is, in the hierarchy of cues that is accessed by the search process of a decision-making strategy (see also Meder et al., 2010). To the extent that the feedback about whether a decision was correct or incorrect leads to an updating of cue validities, the cue ordering might consequently be updated as well. In this sense, causal beliefs can be perceived as hypotheses to be tested and updated with empirical data (see also Koslowski, 1996; Koslowski & Masnick, 2002). Consequently, causal beliefs might act as hypotheses that constrain cue selection to make decisions—whether these beliefs are confirmed or disconfirmed depends on the experience with the selected cues in the environment. In line with this result, Fugelsang, Stein, Green, and Dunbar (2004) showed that even scientists are not immune against overvaluing their initial beliefs when testing their hypotheses on new data. Their results reveal that only great amounts of disconfirming evidence have the power to affect the original theory proposed by researchers.

Are our conclusions about the beneficial effect of causal knowledge restricted to the family of fast and frugal heuristics? Our intuition is that the present approach might also be extended to other decision strategies. Causal knowledge possibly could also help to reduce the computational complexity inherent in more demanding strategies for making decisions such as the weighted additive model (WADD)—a compensatory strategy that uses cue validities as weights (Martignon & Hoffrage, 2002). However, contrary to fast and frugal heuristics, WADD and other compensatory strategies do not model the search process. That is, they strictly assume that all the relevant and necessary information to make decisions is available to the decision maker. Yet, as we mentioned above, this is, in fact, often not the case and thus people would have to actively search for information. We find it difficult to see how people using such compensatory strategies could use their causal knowledge to select from the wide range of candidate cues in the environment those that are highly valid. If cue search and selection is no longer driven by the strategy that is used, how would causal knowledge aid learning of cue validities? Briefly, simplification is not an inherent feature of these decision models. Consequently, in their present form, they could not benefit from the advantages of causal knowledge we pointed out above. The belief revision model (Catena et al., 1998; Catena, Maldonado, Perales, & Cándido, 2008), for instance, tries to integrate prior beliefs with empirical evidence: A prior belief serves as an equivalent to causal knowledge, whereas new empirical evidence stands for the presented covariation data. Increasing the initial prior belief/ causal knowledge and decreasing the reliability of the empirical evidence/covariation data can explain the strong impact of previous beliefs on causal decisions via simulation (see also Garcia-Retamero et al., 2009). The presence of causal knowledge is vital as it directs the search for information, facilitates the learning of cue validities, and improves decision accuracy. Not providing such knowledge in an experiment will make decision makers appear less competent than they would be in their natural environment in which such information is frequently available.

In fact, causal knowledge has a large impact on peoples' daily decisions and behavior. Consider stereotypes, for example. Stereotypes represent commonly shared causal knowledge about a certain social group that indicate their attributes, roles, and behaviors (Gill, 2004). Once a stereotypic belief is implemented in someone's perception of the world, it is highly persistent to contradicting information or to breaking the "stereotypic habit" [85]. People stick to their initial beliefs for quite some time even if these are not supported by the environment. Extended practice in non-stereotypic responding, however, can lead to a decrease in the activation of stereotypes (Kawakami, Dovidio, Moll, Hermsen, & Russin, 2000)—which is similar to the pre-training in one of our studies.

Another example comes from marketing strategies: living in a consumer society, most people are overwhelmed by the amount of certain products offered (e.g., laptop computers).People might therefore search only for specific qualities of a product, and in this case advertisement starts to play a significant role in "facilitating" peoples' decision making processes (Malony, 2000). Advertisements aim to provide customers with causal knowledge connecting a cue with a criterion (e.g., a brand with quality) and "help" them to find the right product out of the confusing market. Adopting a more general perspective, it becomes obvious that not only companies but also political parties or other organizations try to provide the public with causal information to influence decision making (Pratkanis & Aronson, 2001). For instance, even though the power of propaganda has often been underestimated, it is frequently used as a tool for social control and political indoctrination (Chapman, 2000). Our research does not suggest that consumers and citizens should suppress their causal knowledge and become naïve scientists examining all empirical data in the environment. First, in light of the advantages of causal knowledge this would not be desirable, and second, in light of the empirical evidence reviewed above it would be naïve to believe that this was possible in the first place. However, people could benefit from being aware of the strong impact of their causal knowledge on decisions and scrutinize their initial beliefs more often—especially when judging others or making important life decisions. In general, it should now be clear that decisions are not only based on what can be learned, following a bottom-up approach, by inspecting the empirical evidence in the environment. Rather, decisions are also influenced, in a top-down fashion, by causal knowledge. Therefore, any approach that tries to explain decision making should incorporate peoples' capacity to learn about causal structures.

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Introduction: Overview of the studies

Overview of the studies

The present thesis aims to map the influence of causal beliefs in decision making and causal judgments. In line with the introduction (Garcia-Retamero, Hoffrage, Müller, & Maldonado, 2010), the following studies act on the assumption that people do not process all the available information in the environment but use their causal knowledge to focus on a small subset of highly predictive cues. Causal knowledge may thereby also be an important factor to facilitate the learning of cue validities. Consequently, the access to causal information may reduce the complexity of the environment when making decisions and causal judgments.

To analyze the influence of causal beliefs in decision making and causal judgments, the present studies applied a two-alternative forced-choice task, in which four cues described the outcome. These cues differed in their causal relation (i.e., causal beliefs) with the outcome and the validity information provided throughout the decision task (i.e., empirical evidence). Finally, an important aspect of this thesis is the distinction between decisions and judgments, two terms that are often mentioned interchangeably. As recent literature extended the use of causal models to decision making (Sloman & Lagnado, 2006), the aim of the present studies is to disentangle the interplay between decision making and causal judgments trying to account for these two processes with one single theoretical model.

Chapter 1 (Garcia-Retamero, Müller, Catena, & Maldonado, 2009) focuses on the influence of causal beliefs and empirical evidence in decision making and causal judgments thereby hypothesizing that causal beliefs would have a stronger influence on causal judgments than on decision making. Furthermore, the authors hypothesized that the integration of empirical evidence into decisions and causal judgments can be facilitated when participants are provided with pre-training that does not include any causal information. In any other case, the authors expected that the access to causal information would influence decisions and causal judgments beyond given new empirical information.

Chapter 2 (in press as Müller, Garcia-Retamero, Cokely, & Maldonado) aimed to extend the understanding of the dynamic interplay between causal beliefs, decision making, and causal judgments. The main hypothesis of this study was that participants could improve their assessment of the empirical evidence in decision making with greater experience and the availability of cues that varied widely in their predictive accuracy. As previous research indicates differences between observations and interventions (Hagmayer & Sloman, 2009; Meder, Hagmayer, & Waldmann, 2008) causal information might also impact decisions differently than judgments. In this vein, the authors aimed to disentangle factors that may explain a disassociation between causal judgments and decisions.

Chapter 3 (submitted as Müller, Garcia-Retamero, Galesic, & Maldonado) focused on the influence of causal beliefs in decision making and causal judgments in two different domains: medical and financial. As most research on judgment and decision making covers only single domain settings, the authors questioned the validity of such findings. They hypothesized that causal beliefs would be stronger in the medical than the financial domain. This hypothesis was based on two assumptions: First, the people might perceive a lower variability of cue validities in the medical compared to the financial domain and therefore would be able to assess empirical evidence much easier in the latter one. Second, causal beliefs might be stronger in the medical domain, as this domain may imply life-threatening consequences. The authors further hypothesized that the influence of causal beliefs would be higher in causal judgments than decisions, as previous research indicated a dissociation between these processes.

Chapter 4 (submitted as Müller, Garcia-Retamero, Catena, Perales, Galesic, & Maldonado) mapped the interplay between the judgment frequency (i.e., the frequency that people make a "causal judgment") and the (in)flexibility of causal beliefs as a function of domain-specific information. The authors hypothesized that repeated judgments would adjust to the empirical evidence provided in the two-alternative forced-choice task. To assess the degree that causal beliefs are sensitive to anchoring-and-adjustment effects in each domain, the authors manipulated judgment frequency and causal information provided in the experimental task. Finally, the article tries to explain causal judgments and decision making processes with a theoretical model that integrates the strength of a causal beliefs and the reliability of new evidence.

The ***summary and conclusion*** integrates the accumulated evidence and novel insights presented in the studies of the thesis. This summary offers a brief description about the main findings presented in chapter 1, 2, 3 y 4. Furthermore, it provides a theoretical framework that tries to integrate empirical evidence and the strength of causal beliefs to account not only for decision making but also causal reasoning. Finally, some limitations of the present work and possibilities for future research are discussed.

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CHAPTER 1

The power of causal beliefs and conflicting evidence on causal judgments and decision making[5]

Abstract

In two experiments, we investigated the relative impact of causal beliefs and empirical evidence on both decision making and causal judgments, and whether this relative impact could be altered by previous experience. Participants had to decide which of two alternatives would attain a higher outcome on the basis of four cues. After completing the decision task, they were asked to estimate to what extent each cue was a reliable cause of the outcome. Participants were provided with instructions that causally related two of the cues to the outcome, whereas they received neutral information about the other two cues. Two of the four cues—a causal and a neutral cue—had high validity and were both generative. The remaining two cues had low validity, and were generative in Experiment 1, but almost not related to the outcome in Experiment 2. Selected groups of participants in both experiments received pre-training with either causal or neutral cues, or no pre-training was provided. Results revealed that the impact of causal beliefs and empirical evidence depends on both the experienced pre-training and cue validity. When all cues were generative and participants received pre-training with causal cues, they mostly relied on their causal beliefs, whereas they relied on empirical evidence when they received pre-training with neutral cues. In contrast, when some of the cues were almost not related to the outcome, participants' responses were primarily influenced by validity and—to a lesser extent—by causal beliefs. In either case, however, the influence of causal beliefs was higher in causal judgments than in decision making. While current theoretical approaches in causal learning focus either on the

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effect of causal beliefs or empirical evidence, the present research shows that both factors are required to explain the flexibility involved in human inferences.

Introduction

Many decisions in daily life are based on choices that often include an uncertain outcome about future states of the world. Imagine that you have to decide between alternative ways to invest your money, choose a restaurant, or choose between different hypothetical partners from an online dating- agency—the available information will always be limited. Causal beliefs can help to come to a satisfying conclusion (e.g., which bank bears the highest interest or which pill is more likely to relieve a headache). Taking the view of a consumer, for instance, it is often believed that high product quality is associated with high production costs, resulting in higher prices than paid for an average product. Thus, a customer may believe in the probability that the price-level predicts the quality, exclusiveness, or abstract value of a purchased object due to its production expenses (Alba, Broniarczyk, Shimp, & Urbany, 1994). Causal beliefs can be derived from one's own previous experiences purchasing "high quality products" or from advertisements by high-profile people (Garcia-Retamero, Takezawa, & Gigerenzer, 2008, 2009). Applied to the example of relieving a headache, our previous experience with a certain drug or the recommendation by a physician will most likely guide our choice of which pill to take.

The quality of a decision is related to the capacity to apply inferences about the future drawn from experiences verifying or falsifying previous causal beliefs (Fugelsang & Thompson, 2003; Garcia-Retamero, Hoffrage, & Dieckmann, 2007; Garcia-Retamero, Hoffrage, Dieckmann, & Ramos, 2007; Perales, Catena, & Maldonado, 2004). However, are naïve scientists—or consumers—always that rational? This question is examined in two experiments. The main aim of these experiments was to analyze the relative impact of causal beliefs and empirical evidence on decision making and causal judgments, and above all, whether this relative impact can be altered by previous experience.

Reliance on empirical evidence can be influenced by prior causal beliefs to a great extent (Garcia- Retamero & Dhami, 2009). Interestingly, findings analyzing the influence of previous beliefs on people's judgments yield contrary results: whereas some researchers (e.g., Alba et al., 1994; Baumgartner, 1995; Wright & Murphy, 1984) arrive at the conclusion that previous beliefs boost our covariation assessment, others (e.g., Billman, Bornstein, & Richards, 1992; Nisbett & Ross, 1980) claim that their influence is rather disrupting, and that objective correlations can only be assessed correctly when relevant prior beliefs are absent or congruent with the empirical evidence (Alloy & Tabachnik, 1984). Prior causal beliefs, for instance, can increase the accuracy of judgments if the causal beliefs are used as hypotheses tested on data (Baumgartner, 1995; Garcia-Retamero, 2007; Garcia-Retamero & Hoffrage, 2006, 2009). Assessments of relationships between events that are guided by beliefs, such as the relationship between price and quality, are more accurate than belief-free judgments about abstract stimuli, especially when the data are noisy (Baumgartner, 1995; Wright & Murphy, 1984). Therefore, causal beliefs could have beneficial effects.

In contrast, research also shows that identical objective correlations can be judged very differently when previous knowledge about the relationship between a cause and an effect conflicts with empirical evidence. For instance, participants in a study by Evans, Clibbens, Cattani, Harris, and Dennis (2003; see also Evans, Clibbens, & Harris, 2005) were provided with information compatible, incompatible, or neutral with their beliefs. The results showed that previous beliefs only improved judgments when the empirical evidence provided in the task was compatible with these beliefs. An explanation of this result may be that participants overvalued prior beliefs when assessing actual contingencies, which therefore led to a ‘‘confirmation bias” (Chapman & Chapman, 1967; Fugelsang & Thompson, 2003; Klayman, 1995). In that way, only information confirming prior beliefs is taken into account, whereas conflicting information is ignored.

A close look at the literature on causal learning shows various attempts to explain the relation between causal beliefs and covariation information (see Perales & Catena, 2006, for an overview; see also Ahn & Kalish, 2000). According to Fugelsang and Thompson (2003), for instance, people first recruit knowledge about plausible causes of an effect from three possible sources: provided instructions, perceived covariance between the cause and the effect, and beliefs about the mechanisms interconnecting them. Holding this information, the new empirical evidence (i.e., covariation-based data) is processed and evaluated. Searching for plausible causes, therefore, helps to reduce and select the set of candidates for which covariation is considered (see also Spellman, Price, & Logan, 2001). At this step, causal knowledge is also the main factor guiding the interpretation of covariation in terms of a causal or mere spurious relationship.

A recent theoretical attempt to account for the influence of previous knowledge on evaluations of empirical evidence is the ***Belief Revision Model*** (Catena, Maldonado, & Cándido, 1998; Maldonado, Catena, Cándido, & Garcia, 1999). The model addresses the mechanism of how new covariation information is integrated into a cause-effect relationship. Belief updating is processed through a function representing the integrative causal judgment (J_n) as a sum of the prior belief (J_{n-1}) and its discrepancy from

NewEvidence (computed as weighted ΔD; Catena et al., 1998) multiplied with ***ß*** (codifying the reliability of the covariation evidence's origin):

$$\boldsymbol{J}_{\mathrm{n}} = \boldsymbol{J}_{\mathrm{n-1}} + \boldsymbol{ß}(\boldsymbol{NewEvidence} - \boldsymbol{J}_{\mathrm{n-1}}) \qquad (1)$$

Whether the reasoner has a previous belief is reflected in a $\boldsymbol{J}_{\boldsymbol{n}-1}$ non-zero value, whereas a value of zero reflects no a priori cause-effect beliefs. The model explains successfully the influence of causal beliefs on causal judgments (Catena et al., 1998; Maldonado et al., 1999) and was extended recently to multiple cause scenarios (see Catena, Maldonado, Perales, & Cándido, 2008; Perales, Catena, Maldonado, & Cándido, 2007).

In contrast to the literature on causal learning, there is a dearth of published research on the influence of causal beliefs in decision making (Garcia-Retamero & Hoffrage, 2006, 2009). One of the few studies on the issue was conducted by Garcia-Retamero, Wallin, and Dieckmann (2007). Participants in this study were asked to decide which of two alternatives would have a higher criterion value (the outcome) and could inspect up to four cues (i.e., four properties describing the alternatives) to make this decision. Results showed that when causal information about some cues was available, participants preferred to search for these cues first, especially if they had high predictive power, and to base their decisions on them. Participants also became more frugal (i.e., they searched fewer of the available cues), made more accurate decisions, and were more precise in estimating the predictive power of the cues than was the control group, which did not receive causal information. Overall, these results support the hypothesis that causal knowledge aids decision making and helps people identify highly predictive cues.

To date, research about the effect of causal beliefs on the evaluation of empirical evidence focused rather independently either on decisions (e.g., Garcia-Retamero et al., 2007) or causal judgments (e.g., Catena et al., 2008; Fugelsang & Thompson, 2003).

The aim of the present work was twofold: first, to investigate the relative influence of causal beliefs and empirical evidence on decisions and causal inferences, and to determine which of these two processes has higher impact, and, secondly, to analyze whether a previous experience can modify the relative influence of causal beliefs and empirical evidence on decision making and causal judgments. More specifically, this research aimed to discover the extent to which previous experience can enhance or abolish the influence of causal beliefs.

Overview of the experiments

In two experiments and common to all groups, participants went through a series of two-alternative forced-choice tasks, which were phrased as medical diagnostic tasks. In these tasks, participants were asked to choose which of two patients would show a higher degree of allergic dermatitis (the outcome). To make each decision, participants could search for information concerning up to four cues that described both patients by clicking little boxes on the computer screen to retrieve that information. The cues specified whether the patients used a certain shower gel, ingested a prescription drug, were bitten by an insect, or worked in a certain industry (see Appendix and procedure). These properties are common for predicting allergic dermatitis (see, e.g., Hogan, 1994). After completing all decisions, participants were asked to estimate to what extent each cue was a reliable cause of the outcome (i.e., a causal judgment) on a scale ranging from 10 to 10. A positive rating implied that the cue causes the outcome, whereas a negative rating stood for the cue preventing the outcome. A zero rating implied that the cue had no effect on the outcome. To analyze the influence of causal beliefs, participants were told via experimental instructions that two of the four cues were causally linked to the outcome, henceforth referred to as the causal cues. Specifically, the instructions suggested an underlying causal mechanism that could explain why there is a statistical relationship between the two causal cues and the outcome. The remaining two cues were neutral and participants were provided with instructions that did not link these cues causally to the outcome. For example, participants were informed that the patients could have ingested a certain prescription drug (Rifastan pills), described as “an antibiotic which could lead to skin swelling” when the cue was causal, or as “vitamin C tablets, which are crucial for sight” when the cue was neutral. A pretest confirmed that causal—but not neutral—cues were indeed perceived as having a strong causal power (see Appendix).

To analyze the influence of the empirical evidence, cue validities were manipulated within-subjects. The validity of a cue is the probability that this cue leads to the correct decision given that it discriminates between the alternatives (i.e., it is present in one of the patients and absent in the other; Gigerenzer, Hoffrage, & Kleinbölting, 1991; see also Gigerenzer, Todd, & the ABC Research Group, 1999). Validity above 0.5 refers to a cue predicting the outcome (i.e., it is a generative cause). Validity set below 0.5 and above 0 refers to a cue predicting the absence of the outcome or a cue not related to that outcome. In the decision phase of the following experiments, two of the four cues (one causal and one neutral cue) had high validity. The remaining two cues (the remaining causal and the neutral cues) had low validity. In sum, to make a decision, participants could inspect four possible cues: a causal high-validity cue (CH), a causal low-validity cue (CL), a neutral high-validity cue (NH), and a neutral low-validity cue (NL). In this way, it was possible to look for the differential effect of causal beliefs and empirical evidence on both decision making during the tasks and subsequent causal judgments.

Experiment 1

Beyond the investigation of the relative influence of causal beliefs on decision making and causal judgments, Experiment 1 tested whether previously experienced evidence plays an additional role in altering these processes. The manipulation was carried out by pre-training selected groups of participants. Members of the causal control group did not go through any pre-training (see Table 1). In contrast, in the pre-causal and pre-neutral groups, participants were provided with a pre-training experience before the decision phase of the experiment. In the pre-training, participants in the pre-causal group were only presented with two causal cues, which differed in their cue validity (CH, CL); participants in the pre-neutral group only received two neutral cues with different cue validities (NH, NL). Participants who were exposed to pre-training received two additional cues in the decision phase. For participants in the causal control group, however, all cues were new.

Table 1. Design of Experiments 1 and 2.

Experimental Group	Instructions	Pre-training phase	Instructions	Decision phase
Experiment 1				
Causal control group	–	–	Causal	CH, CL, NH, NL
Pre-causal group	Causal	CH, CL	Causal	CH, CL, NH, NL
Pre-neutral group	Neutral	NH, NL	Causal	CH, CL, NH, NL
Experiment 2				
Causal control group	–	–	Causal	CH, CL, NH, NL
Pre-causal group	Causal	CH, CL	Causal	CH, CL, NH, NL
Pre-neutral group	Neutral	NH, NL	Causal	CH, CL, NH, NL
Neutral control group	–	–	Neutral	NH, NL, NH, NL

Note: CH and CL refer to a causal high-validity and a causal low-validity cue, respectively; NH and NL refer to a neutral high-validity and a neutral low-validity cue, respectively.

In line with the research reviewed above (e.g., Fugelsang & Thompson, 2003; Garcia-Retamero et al., 2007), we expected that a lack of pre-training—as in the causal control group—would result in a higher influence of causal beliefs than of cue validities on participants' decisions and causal judgments. Groups receiving pre-training, however, should be primarily affected by the previous experience in their evaluation of the new evidence. Thus, pre-training with causal cues (in the pre-causal group) was expected to increase participants' reliance on causal cues (regardless of their cue validity). In contrast, when only neutral cues were presented during the pre-training (in the pre-neutral group) individuals were expected to primarily rely on highly valid cues (regardless of whether the cues are causal or neutral). Briefly, participants in the pre-causal and pre-neutral groups were supposed to use the information acquired in the pre-training as an anchor to evaluate the new empirical evidence provided in the decision phase of the experiment. Dependent on the pre-training, conflicting empirical evidence was assumed to be disregarded, whereas confirming data should easily be integrated. This pattern was expected to appear in participants' decisions and causal inferences.

Method

Participants. Forty-five students (39 women and 6 men, average age 22 years, range 19–37) from the University of Granada were randomly assigned to one of three equally sized groups (pre-causal, pre-neutral, causal control; n = 15). The computerized task was conducted in individual sessions and lasted approximately 1 h. Participants received course credit for their participation in the experiment.

Procedure. Participants first read the instructions of the experiment. In a series of two-alternative forced-choice tasks (i.e., the decision phase of the experiment), participants were then asked to choose between two patients (displayed column-wise) by selecting the one who would show a higher degree of allergic dermatitis, on the basis of several properties (cues) describing those patients. The order in which the four cues were presented on the screen was fixed for each participant, but varied randomly between participants, and inter-cue correlation was almost zero. Whenever a box was selected to gain information about a cue, the cue values of both patients appeared simultaneously on the screen and remained visible until a decision was made. Participants could search for as many cues as they wanted, but they had to look up at least one cue to make a decision.

After searching for information in each trial, participants made a decision by clicking on a button (i.e., they selected one of the two patients), and subsequent feedback about the correctness of the decision was displayed. They made 60 decisions with no time constraints (i.e., three blocks of 20 trials each). For each participant, the same set of trials was presented within each block, but in random order. In addition, participants were provided with an account reflecting their decision behavior. The current balance of their account was always visible on the computer screen and participants were told to attain the maximum points. For each cue looked up, 1 point was deducted from participants' overall payoffs. In addition, they could gain seven points for each correct decision.

Once the 60 decisions were completed, participants had to judge to what extent each of the four cues was a reliable cause of the outcome on a scale ranging from 10 to 10. A positive rating implied the cue caused the outcome, whereas a negative rating implied the cue prevented the outcome; a zero rating implied the cue had no effect on the outcome. Before the decision phase of the experiment, some participants went through a pre-training phase in which they also made 60 decisions (see Design).

Design. The first (within-subjects) manipulation involved cue validities and instructions about the cues. In the decision phase of the experiment, participants were given information that causally related two of the cues to the outcome, whereas the two remaining cues were neutral. Which cues were causal and which were neutral was counterbalanced across participants. Furthermore, two of the cues had a high validity (i.e., 0.85) and the other two had a low validity (i.e., 0.65), also counterbalanced across participants. Taken together, to make a decision, participants could inspect up to four cues: a causal high-validity (CH), a causal low-validity (CL), a neutral high-validity (NH), and a neutral low-validity (NL) cue. All four cues had a discrimination rate of 0.56. The discrimination rate of a cue is the number of pair comparisons in which the alternatives have a different value on that cue (i.e., the number of occasions in which that cue is present in one patient and absent in the other; Gigerenzer & Goldstein, 1996). The presence of each cue was independent of that of the other cues (i.e., cue inter-correlation was almost zero).

The second (between-subjects) manipulation concerned the pre-training before the decision phase of the experiment. Participants in the causal control group did not receive any pre-training before the decision phase of the experiment. However, the pre-causal and pre-neutral groups were exposed to pre-training with two causal or two neutral cues, respectively. The validity of the cues in the pre-training was either high (0.85) or low (0.65). In contrast to the decision phase of the experiment, participants did not have to search for cues in the pre-training phase, and cue values for each patient were automatically displayed. No search costs were imposed in this phase to allow participants to learn the cue validities. Similar to the decision phase, participants in both groups were asked to make 60 decisions, and outcome feedback was provided.

Results and discussion

The analysis contains three main parts: first, we examined participants' decisions based on the selected cues. Subsequently, we reported results on causal judgments about the cues. Finally, we tested whether our findings were indeed due to the specific procedure we used in the experiment. Post hoc comparisons in all experiments were conducted with Fisher's LSD, alpha-level 0.05.

As the upper panel of Fig. 1 shows, participants in the pre-causal and causal control groups decided more often in favor of causal cues over neutral cues. In contrast, participants in the pre-neutral group decided equally often in favor of the causal and the neutral cues. A 3 (Group) × 2 (Causal Beliefs) × 2 (Cue Validity) repeated measures analysis of variance (ANOVA) on participants' decisions supported these results. The dependent variable measured the proportion of trials during the decision phase in which participants decided in favor of a cue—out of all trials in which that cue was looked up and was found to discriminate between the two alternatives. The ANOVA yielded significant main effects of Group, $\boldsymbol{F}(2, 42) = 12.65$, $\boldsymbol{p} < 0.001$, Causal Beliefs, $\boldsymbol{F}(11, 42) = 47.30$, $\boldsymbol{p} < 0.001$, and Cue Validity, $\boldsymbol{F}(1, 42) = 84.64$, $\boldsymbol{p} < 0.001$. Causal cues were more often selected than neutral ones. In addition, high-validity cues were more often selected than low validity ones. The interaction between Group and Causal Beliefs, $\boldsymbol{F}(22, 42) = 10.36$, $\boldsymbol{p} = 0.001$, was also significant. Simple effects analyses of this interaction showed that participants in the pre-causal and causal control groups decided more often in favor of causal cues over neutral cues, $\boldsymbol{F}(1, 14) = 49.476$, $\boldsymbol{p} < 0.001$ and $\boldsymbol{F}(1, 14) = 28.306$, $\boldsymbol{p} < 0.001$, respectively, indicating a clear effect of causal beliefs beyond cue validity. In contrast, participants in the pre-neutral group decided equally often in favor of the causal and the neutral cues, $\boldsymbol{F}(1, 14) < 1$; here, the effect of previous causal beliefs was removed and decisions relied mainly on cue validity. On the other hand, differences between groups were observed with both causal and neutral cues, $\boldsymbol{F}(2, 42) = 16.735$, $\boldsymbol{p} < 0.001$ and $\boldsymbol{F}(2, 42) = 3.915$, $\boldsymbol{p} < 0.03$, respectively.

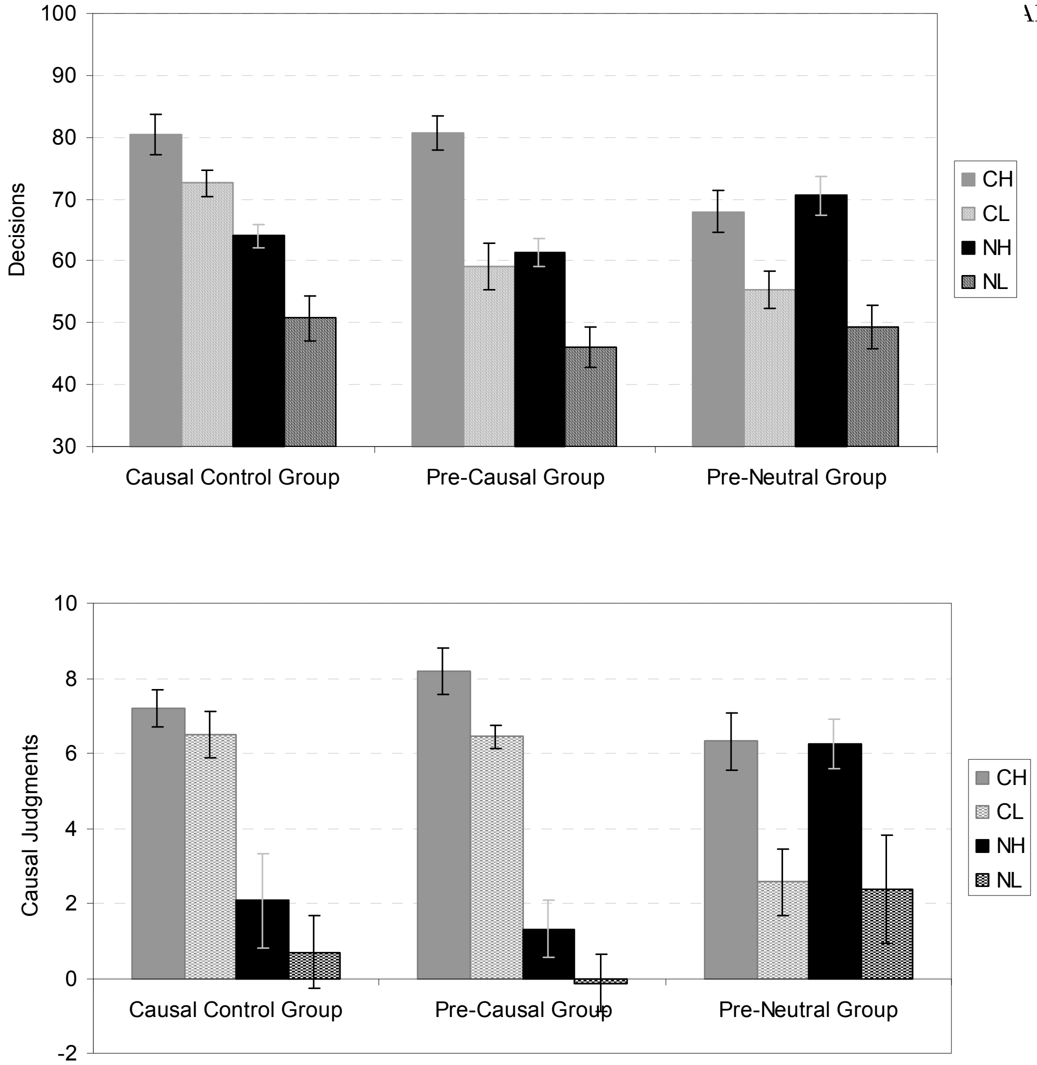

Fig. 1. Upper panel: percentage of trials in which participants decided in favor of the causal high-validity cue (CH), causal low-validity cue (CL), neutral high-validity cue (NH), and neutral low-validity cue (NL) in the three experimental groups in Experiment 1. Error bars represent one standard error.
Lower panel: causal judgments about the causal high-validity cue (CH), causal low-validity cue (CL), neutral high-validity cue (NH), and neutral low-validity cue (NL) in the three experimental groups in Experiment 1. Error bars represent one standard error.

Post-hoc LSD comparisons showed that the causal cues were favored more often by the pre-causal and causal control groups than by the pre-neutral group. Neutral cues, however, were more frequently favored by the pre-neutral group than by the pre-causal group. No other differences were observed in the analyses.

From these results, we can conclude that participants' decisions were guided by causal beliefs and by empirical evidence (cue validity). The absence of any pre-training (in the causal control group) or pre-training with causal cues (in the pre-causal group) led to a clear preference for the causal cues. In contrast, when participants experienced pre-training with valid cues that were not causally linked to the outcome (in the pre-neutral group), the causal instruction about the cues did not have any substantial influence on participants' decisions (i.e., results were independent of the causal status of the cues).

In line with the results about decisions, the lower panel of Fig. 1 shows that causal cues were evaluated as more reliable causes of the outcome in the pre-causal and causal control groups than in the pre-neutral group. Additionally, causal judgments were higher for the causal than for the neutral cues in the pre-causal and causal control groups. The ANOVA, 3 (Group) × 2 (Causal Beliefs) × 2 (Cue Validity), on participants' causal judgments supported these results. The analysis yielded a significant main effect of Causal Beliefs, $\boldsymbol{F}(1, 42) = 33.376$, $\boldsymbol{p} < 0.001$ —indicating a preference for causal over neutral cues in causal judgments—, Cue Validity, $\boldsymbol{F}(1, 42) = 20.217$, $\boldsymbol{p} < 0.001$—indicating a preference for high over low-validity cues—and an interaction between Group and Causal Beliefs, $\boldsymbol{F}(2, 42) = 8.197$, $\boldsymbol{p} < 0.001$. The interaction between Group and Cue Validity was nearly significant, $\boldsymbol{F}(2, 42) = 3.093$, $\boldsymbol{p} = 0.056$. Simple effects analyses of the interaction between group and causal beliefs yielded differences between groups in the causal but not in the neutral cues, $\boldsymbol{F}(2, 42) = 5.629$, $\boldsymbol{p} < 0.007$, and $\boldsymbol{F}(2, 42) = 1.22$, $\boldsymbol{p} = 0.304$, respectively. Post-hoc LSD tests showed that causal cues were evaluated as more reliable causes of the outcome in the pre-causal and causal control groups than in the pre-neutral group. On the other hand, causal judgments were higher for the causal than for the neutral cues in the pre-causal and causal control groups, $\boldsymbol{F}(1, 14) = 82.896$, and $\boldsymbol{F}(1, 14) = 24.881$, $\boldsymbol{p} < 0.001$. Between group differences were also observed in high-validity cues, $\boldsymbol{F}(2, 42) = 3.414$, $\boldsymbol{p} = 0.0423$. Causal judgments in the pre-neutral group were higher than those in the pre-causal and causal control groups. Moreover, causal judgments for high-validity cues were higher than those for low-validity cues for both pre-trained groups, $\boldsymbol{F}(1, 14) > 10.414$, $\boldsymbol{p} < 0.007$.

In a further step, we wanted to test whether our results were indeed related to the experimental procedure we used. Therefore, we first examined differences between participants' experienced and programmed cue validities using a 3 (Group) × 2 (Causal Beliefs) × 2 (Cue Validity) repeated measures ANOVA. As expected, neither main effects nor interactions were significant (min $\boldsymbol{p} > 0.27$). This result speaks against any response biases induced by our procedure. Secondly, we examined whether participants searched more frequently for causal than for neutral cues. We submitted the number of occasions that a cue was explored to a 3 (Group) × 2 (Causal Beliefs) × 2 (Cue Validity) repeated measures ANOVA. This analysis yielded only a significant main effect of Cue Validity, $\boldsymbol{F}(1, 42) = 10.312$, $\boldsymbol{p} < 0.003$. High-validity cues were looked up more frequently than low-validity cues, but no differences among groups could be observed. Thus, we can rule out that the effect of previous beliefs was based on the frequency of cue-exploration. Moreover, about 80% of our participants explored each cue more than 15 times. This is a significant number of observations that enabled participants to accurately estimate the causal impact of a cue.

Finally, we examined the relationship between participants' causality judgments and decisions. To do that, we computed the canonical correlation between the two sets of dependent variables. Canonical R was 0.86, $\chi^2(16) = 17.210$, $\boldsymbol{p} = 0.373$. Additionally, the higher simple linear correlation between causal judgment and decisions was −0.38.

Taken together, results in Experiment 1 showed that causal beliefs were the main factor guiding participants' causal judgments and decisions in the pre-causal and causal control group: when participants had previous beliefs about the possible causal mechanism that links the cues with the outcome, they disregarded the cue validity while making causal judgments. In contrast, when they received pre-training with the neutral cues, participants relied strongly on the validity of the cues, regardless of their causal beliefs. Interestingly, causal judgments and decision making appeared to tap different psychological mechanisms, as no correlation was observed between the two variables. To test this hypothesis, we conducted a second experiment using cues with very high- and low validity and, in addition, tested a new control group of participants who only received neutral cues.

Experiment 2

The aim of this experiment was to replicate the findings of Experiment 1, but this time using cues that differ to a greater extend in their validities. We further intended to examine participants’ ability to detect cue validities when no pre-training was provided. For the latter purpose, a new control group (i.e., the neutral control group) was introduced. Participants in this group did not receive any pre-training and could base their decisions and causal judgments only on neutral cues with either high or low validity. This new control group, therefore, did not receive any causal information about the cues and was expected to show the net influence of empirical evidence at baseline. The main goal of Experiment 2 was to test whether a greater difference between the high and low validity of the cues could reduce the influence of causal beliefs on participants’ decisions or causal judgments. Would participants who only received neutral cues and no pre-training be able to rely on cue validities to make decisions and causal inferences? Further, would participants experiencing no pre-training or pretraining with the causal cues still rely on such cues when one of them had a very low validity? The answers to these questions have theoretical implications for decision making and causal learning.

Method

Participants. Sixty-four students (54 women and 10 men, average age 21 years, range 18–29) from the University of Granada participated in the experiment. Participants were randomly assigned to one of four equally sized groups (n = 16). The computerized task was conducted in individual sessions and lasted approximately 1 hr. Participants received course credit for their participation in the experiment.

Procedure and design. The task and the procedural details of Experiment 2 were identical to those of Experiment 1 for the control-causal, pre-causal, and pre-neutral group. The only difference was that high and low validity cues had a programmed validity of 0.90 and 0.10, respectively (i.e., cues were generative or almost not related to the outcome). The mean of the validity that participants observed over all conditions was 0.90 for high-validity cues (range = 0.94–0.82) and 0.07 for low-validity cues (range: 0.04–0.13). In this experiment, all four cues had a discrimination rate of 0.59 and inter-cue correlation was close to zero. In addition, a fourth group of participants was introduced (the neutral control group). Participants in this group did not experience any pre-training and could base their decisions only on four neutral cues: two with high (0.90) and two with low (0.10) validity.

Results and discussion

As the upper panel of Fig. 2 shows, participants in all groups often decided in favor of neutral cues. A 4 (Group) × 2 (Causal Beliefs) × 2 (Cue Validity) repeated measures ANOVA on participants' decisions supported these results. The analysis yielded a significant main effect of Cue Validity, $\boldsymbol{F}(3, 42) = 28.286$, $\boldsymbol{p} < 0.001$, and an interaction between the three factors, $\boldsymbol{F}(3, 42) = 3.799$, $\boldsymbol{p} < 0.02$. The analysis of this interaction showed significant effects of Cue Validity in the pre-causal, pre-neutral, and causal control groups, $F(1, 8) = 8.295$, $p < 0.03$, $F(1, 9) = 7.279$, $p < 0.03$, and $F(1, 15) = 10.779$, $p < 0.006$, respectively. In all these cases, participants favored the high-validity cues. Also, the interaction between Causal Beliefs and Cue Validity was significant in the causal control group, $F(1, 15) = 9.888$, $p < 0.007$.

Post-hoc LSD comparisons showed that participants in the causal control group favored the causal high-validity cue followed by the neutral high-validity cue when making decisions. When one of the causal cues was not a reliable predictor of the outcome—setting its validity below 0.5—cue validity exerted a much stronger influence on participants' decisions than causal beliefs did. In fact, the effect of causal beliefs in the pre-causal and causal control groups was lower that in the first experiment (i.e., participants in such groups still preferred to decide in favor of the causal than the neutral high-validity cue). Overall results indicated that the manipulation of cue validity almost removed the effect of previous causal beliefs on decision making.

The lower panel of Fig. 2 shows participants' causal judgments. In general, participants based their causal judgments mainly on causal beliefs, unless they received pre-training with neutral cues or were not exposed to previous beliefs. The ANOVA, a 4 (Group) × 2 (Causal Beliefs) × 2 (Cue Validity), on participants' causal judgments supported these results. The analysis revealed significant main effects of Causal Beliefs, $F(1, 60) = 22.156$, $p < 0.001$, and Cue Validity, $F(1, 60) = 40.749$, $p < 0.001$, and an interaction between Group and Causal Beliefs, $F(3, 60) = 6.580$, $p = 0.001$. Simple effects analysis of this interaction yielded differences between causal and neutral cues only in pre-causal and causal control groups, $F(1, 15) = 17.322$, $p < 0.001$, and $F(1, 15) = 12.671$, $p < 0.003$.

Interestingly, a difference between groups was observed only with neutral cues, $F(3, 60) = 4.897$, $p < 0.005$. According to post-hoc LSD comparisons, this effect can be attributed to the pre-causal group, whose members were less likely to base their causal judgments on the neutral cues compared to all other groups. Thus, again, it appears that decisions and causal judgments tap different psychological processes.

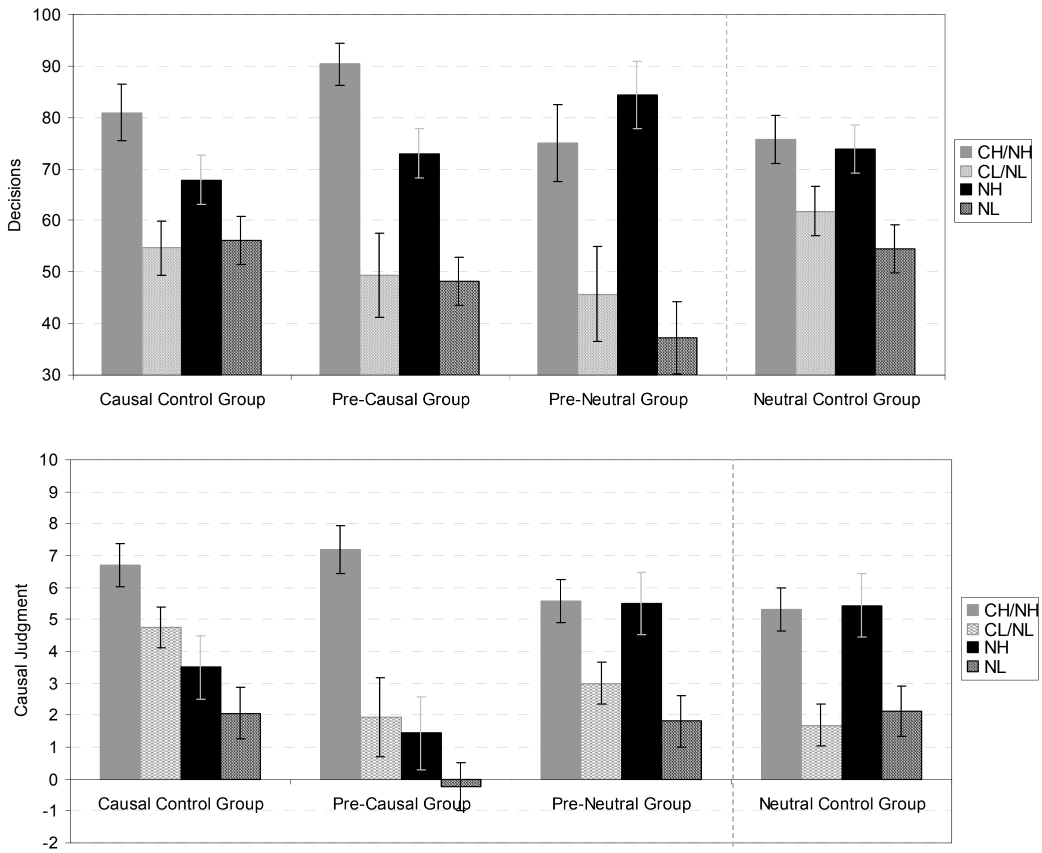

Fig. 2. Upper panel: percentage of trials in which participants decided in favor of the causal high-validity cue (CH), causal low-validity cue (CL), neutral high-validity cue (NH), and neutral low-validity cue (NL) in the four experimental groups in Experiment 2. Error bars represent one standard error. Lower panel: Causal judgments about the causal high-validity cue (CH), causal low-validity cue (CL), neutral high-validity cue (NH), and neutral low-validity cue (NL) in the four experimental groups in Experiment 2. Error bars represent one standard error.

Decisions seemed to be based mainly on cue validity, whereas causal judgments were based mainly on causal beliefs — unless participants received pre-training with neutral cues or were not exposed to any previous beliefs. This result is supported also by the canonical correlation results (canonical R = 0.449, $\chi^2(16) = 19.292$, ***p*** = 0.254, max pair-wise linear correlation = 0.350).

In sum, decision making and causal judgments were primarily influenced by cue validities and—to a lesser extent—by Causal Beliefs. Participants who underwent pre-training with causal cues and those who were lacking any pre-training (but were exposed to previous causal beliefs about some cues) mainly relied on the high-validity cue that was causally linked to the outcome. These participants, however, disregarded the causal low-validity cue —which was almost not related to the outcome. On the other hand, participants who went through pre-training with neutral cues and those who only received neutral cues without any pre-training showed a preference for the high-validity cues, regardless of whether these cues were causal or neutral. In line with the results of Experiment 1, this influence of causal beliefs was higher in causal judgments than in decision making.

General discussion

The purpose of this research was to investigate the relative impact of causal beliefs and empirical evidence on both decision making and causal judgments, and whether this relative impact can be altered by previous experience. The causal judgments results revealed a clear influence of causal beliefs on causal judgments in both experiments. When participants were provided with such beliefs via the experimental instructions and all cues were generative (Experiment 1), causal judgments were mainly based on causal beliefs. Participants who received no pre-training or pre-training with the causal cues, showed this result regardless of cue validities. In contrast, when cues differed substantially in validity and some of the cues were almost not related to the outcome (Experiment 2), participants based their causal judgments on the causal high-validity cue exclusively. Using cues that differed substantially in validity, therefore, altered the influence of causal beliefs.

Our findings about decisions were more diverse but showed a somewhat similar pattern. While participants without any pre-training relied mainly on their causal beliefs—favoring causal over neutral cues—the pre-training with causal cues led to a clear preference for the causal high-validity cue (Experiment 1). Again, increasing the difference between the high and low-validity cues (Experiment 2) reduced the influence of the causal beliefs in both groups. This manipulation led first to decisions in favor of the causal high-validity cue, and second to decisions in favor of the neutral high-validity cue. Finally, when participants received pre-training with neutral cues, causal judgments and decisions were primarily based on the high-validity cues, regardless of whether they were causal or neutral. These results occurred in both experiments, even when individuals experienced neither any pre-training nor any instructions about the causal relation about the cues.

From these findings, we can conclude that participants relied on their causal beliefs by default— especially if the causal cues provided confirming evidence for the causal beliefs and had high validity. Bearing these results in mind, is there any way to erase or minimize this strong impact of existing causal beliefs? When participants received pre-training with neutral cues (i.e., which were not causally linked to the outcome), they became more sensitive to the validity information and were able to discriminate high-validity from low-validity cues. In such cases, additional information about causal mechanisms failed to have further relevance. A possible explanation could be that the pre-training led participants to focus on cue validities and simply to ignore any distracting hint. In a similar vein, when high-validity cues differed substantially from low-validity cues and some of the cues were almost not related to the outcome (Experiment 2), causal judgments and decisions were in line with high-validity cues—especially the cue that was causally linked to the outcome. In sum, when participants received pre-training with neutral cues or when some cues provided information that conflicted with the causal beliefs (i.e., when some of the cues were almost not related to the outcome), participants' responses were mainly influenced by cue validities and—to a lesser extent—by causal beliefs.

These results are in line with previous research claiming that people display a confirmation bias and imply that they are more likely to attend to data consistent with rather than inconsistent with their initial theories (Chapman & Chapman, 1967, 1969; Fiedler, 2000; Klayman, 1995; Wason, 1968; see also Billman et al., 1992 and Evans et al., 2003). Our findings are also compatible with research by Fugelsang, Stein, Green, and Dunbar (2004) who stated that even scientists run the risk of disregarding valuable information when data does not confirm their previous beliefs. Interestingly, these authors also found that even if scientists often show an initial reluctance to consider inconsistent data as ‘‘real,” this initial reluctance could be overcome with repeated observations of the inconsistent data and could finally lead to a modification of their original theories. Scientists only modify their theories, however, if they can replicate the findings contradicting their predictions. Our research sheds more light on this literature showing the appropriate conditions that reduce the initial bias to discount data in favor of initial theories.

The present experiments are unique in their efforts to compare the influence of causal beliefs and empirical evidence in both decision making and causal judgments. Our results showed that causal beliefs have a much higher impact in the latter than in the former. For instance, although participants who were exposed to pre-training with causal cues did not decide very often in favor of a causal cue with low validity, they perceived this cue as a very reliable cause of the outcome. That was especially the case when the cue was generative in Experiment 1. Similarly, in Experiment 2, participants exposed to the causal pre-training decided more often in favor of a high-validity cue that was not causally linked to the outcome than in favor of a causal cue that was almost not related to the outcome. However, they perceived these two cues as equally reliable causes of the outcome. Indeed, our findings support the hypothesis that the psychological mechanisms underlying causal judgments and decision making might not be the same. In contrast to the common practice of studying judgments and decision making independently (e.g., Koehler & Harvey, 2004; Newell, Lagnado, & Shanks, 2007), our experiments highlight the necessity of including these two dependent variables in the same experiment. Future research could further examine differences between judgments and decision making in other domains, as well as seeking to explain the differences we observed between the two variables in our studies.

While current theoretical approaches on causal learning focus either on the effect of causal beliefs (Fugelsang et al., 2004) or of empirical evidence (Garcia-Retamero et al., 2007), the present research shows that both factors are required to explain the flexibility involved in human inferences. In this literature, two theoretical frameworks are predominant. The bottom–up approach assumes that experiencing the relationship between a cue and an outcome helps to generate a causal link (see Cheng, 1997; Spellman, 1996). From this point of view, a cue with high-validity is more likely to be identified as a reliable cause of an outcome than a cue with low validity. In contrast, the top–down approach assumes that people's abstract knowledge about causality (e.g., knowledge about causal mechanism or directionality) shapes how the empirical data are interpreted (Ahn, Kalish, Medin, & Gelman, 1995; Waldmann & Holyoak, 1992; White, 1989). Thus, these theoretical frameworks focus either on the effect of the relationship between the cues and the outcome or on the influence of knowledge about the underlying causal mechanisms, and thus cannot completely explain our results.

Several recent theories have recognized the need to integrate these two approaches. The ***Belief Revision Model*** (Catena et al., 1998, 2008; Maldonado et al., 1999) represents one of these attempts and can explain the results of the experiments reported here (see also Fugelsang & Thompson, 2003; Lien & Cheng, 2000, for other attempts). The Belief Revision Model assumes that causal knowledge serves as an anchor that adjusts the interpretation of new empirical evidence. This anchoring-and-adjustment mechanism, which is similar to that proposed by Hogarth and Einhorn (1992), integrates causal beliefs and empirical evidence (NE) in an additive function –as they both share the same representational basis (see Eq. (1) above). The strength of a causal belief (J_{n-1}) and the reliability (***ß***) of the newly experienced empirical evidence (NE) are responsible for the relative influence of these two factors.

How would the Belief Revision Model fit the results of the experiments reported here? When the cues provided confirming evidence for the causal beliefs (i.e., when all cues were generative) or participants received pre-training with causal cues, the model can fit the strong impact of causal beliefs on participants' responses by increasing the initial value of J_{n-1} (causal beliefs) and decreasing the value of ***ß*** (reliability of empirical evidence). In contrast, the model assumes that empirical evidence incongruent with previous causal beliefs has less impact on participants' responses than experienced confirming information. Therefore, by increasing the reliability of the empirical evidence (b), the model provides a plausible explanation of why participants' responses were based on the cue validities when pre-training with cues that are not causally linked to the outcome was provided, or no causal information was available (in Experiment 2). Thus, the Belief Revision Model not only illustrates participants' responses when the cues provide confirming evidence for the causal beliefs, but also when empirical evidence is conflicting. Briefly, this model considers causal beliefs as a background when empirical data are interpreted, whereupon the empirical evidence could modify people's responses depending on the strength of the causal belief and the perceived reliability of the empirical information.

Finally, Belief updating can be considered from a Bayesian point of view. Such an approach has been adopted by Griffiths and Tenenbaum (2005) in their support model. According to these authors, a causal judgment reflects how certain a reasoner is that the covariational evidence at hand supports the existence of a causal link between the candidate cause and the effect. Such a certainty degree, or support, results from the application of the Bayes rule. In our experiments, however, —given the existence of four cause candidates— the computation of support turns out to be very complex, as the number of possible graphical models is much larger than in a single-case scenario. Specifically, there are sixteen possible causal models (if we do not take the background causes into account). In addition, we need to consider the possibility that the reasoner holds prior beliefs about the a priori likelihoods of those graphs, making the computation even more complex. To our knowledge, the model has not been extended in that way to date. Nevertheless, making predictions from the Bayesian approach to our results would go beyond the scope of this paper.

In sum, what can be learned by these experiments is how much individuals rely on previous causal beliefs when interpreting empirical evidence. As mentioned above, data that confirm previous beliefs would be accepted more easily. This could be adaptive sometimes: Just imagine how many beliefs about the quality of products we have to rely on when entering a supermarket. A re-assessment of all needed products on the basis of empirical evidence would convert a daily shopping tour into a quite intricate long-standing enterprise. However, the time saved through prior knowledge also leads to disadvantages. For instance, propaganda can be perceived as a pre-training experience misusing causal relations with the purpose of ignoring empirical evidence. Similarly, stereotypes are only maintained when experiences with contradictory information are ignored; only a number of findings inconsistent with the initial theory can change beliefs in it. Therefore, a careful reconsideration of one's causal beliefs would always enhance the interpretation of new empirical evidence. Our experiments tried to shed some light on people's causal judgments and decisions when new evidence contained information that confirmed or conflicted with causal beliefs.

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Appendix

Cue	***Causal version***	***Neutral version***
Some patients used Factrosin shower gel	It is made of Peruvian balm, which could irritate the skin	It has a soothing fragrance, which is very pleasant
Some patients ingested Rifastan pills	This is an antibiotic, which could lead to skin swelling	These are vitamin C tablets, which are crucial for sight
Some patients were bitten by the insect Ripl	This is a poisonous spider	This is a regular blue and white butterfly
Some patients work in the industry L.E.D.A.	Abrasive products used to clean toilets are produced in this industry	This industry is crucial for the economy of the city

Note: materials used in Experiments 1 and 2: causal and neutral versions of the four properties that participants could use to determine which of two patients have a higher degree of allergic dermatitis.

In a pre-test, participants (n = 160) were asked to rate to what extent a certain cue causes the outcome— either in its causal or its neutral version—on a scale from 100 (highest positive relationship) to 0 (no relationship). Results show that a cue was judged to have a stronger causal impact on the outcome in its causal version (mean rating = 58.5) than in its neutral version (mean rating = 24.7, $F(1, 78) = 124.5$, $\boldsymbol{p} < 0.001$). In the causal version, there was no difference in how strongly causal cues were perceived to affect the outcome, $\boldsymbol{F}(3, 117) = 1.7$, $\boldsymbol{p} = 0.17$. The same finding appeared for neutral cues, $\boldsymbol{F}(3, 117) = 2.37$, $\boldsymbol{p} = 0.17$.

CHAPTER 2

Causal Beliefs and Empirical Evidence. Decision-Making Processes in Two-Alternative Forced-Choice Tasks[6]

Abstract

Causal beliefs often facilitate decision making. However, strong causal beliefs can also lead to neglect of relevant empirical evidence causing errors in risky decision making (e.g., medical, financial).We investigated the impact of pre-training and post-experience on the evaluation of empirical evidence in a two-alternative medical diagnostic task. Participants actively searched for information about two patients on the basis of four available cues. The first experiment indicated that pre-training can weaken the strong influence of causal beliefs reducing neglect of empirical evidence. The second experiment demonstrated that increasing amounts of empirical evidence can improve people's ability to decide in favor of a correct diagnosis. The current research converges with other recent work to clarify key mechanisms and boundary conditions shaping the influence of causal beliefs and empirical evidence in decisions and causal judgments.

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Introduction

In clinical practice, “beautiful but flawed hypotheses” are often preserved rather than re-examined (Haynes, 2009). Consider the widely promoted screening against prostate cancer (PSA). Evidence indicates that the screening has little to no efficacy and yet carries considerable risks. Nevertheless, many doctors maintain the causal belief that screening is necessary and beneficial leading to the continuation of controversial and potentially dangerous practices (Steurer et al., 2009). Indeed, a wide range of decision makers regularly struggle to account for contradictive empirical evidence in their environment (Fugelsang & Thompson, 2003). Research has documented some strong influences of causal beliefs on decision making as well as causal judgments (Garcia-Retamero, Müller, Catena, & Maldonado, 2009; Hagmayer & Sloman, 2009; Meder, Hagmayer, & Waldmann, 2009; Sloman & Hagmayer, 2006; see Griffiths & Tenenbaum, 2005, for causal Bayesian networks). However, relatively less is known about the influence of causal beliefs on the interplay between decision making and causal judgments. What are the factors that allow one to overcome neglect of contradictive information and improve one’s accuracy in detecting and using empirical evidence?

Decision makers often benefit from causal beliefs when coping with vast amounts of evidence and complexity. Consider a decision about which drug is most likely to relieve a headache. Prior experiences or knowledge (e.g., doctor’s recommendation) can facilitate decision making. Previous research has shown that people cannot fully process all available information in the environment and, therefore, apply mental models about cause-effect relationships (Waldmann, Hagmayer, & Blaisdell, 2006). Consequently, attributions of causal relations frame the final decision and can be perceived as hypotheses that are tested and updated with empirical data (see also Koslowski, 1996).

However, causal beliefs can also have detrimental effects when dealing with contradictive empirical evidence, reducing the impact of covariation information. Such “confirmation bias” is well documented and refers to cases wherein people only accept information that confirms initial causal beliefs. Even scientists and clinicians run the risk of disregarding results that are not in line with previous assumptions (Haynes, 2009; Steurer et al., 2009). As a consequence, evidence contradicting the prior hypothesis tends to be neglected and initial assumptions are resistant to change (Fugelsang, Stein, Green, & Dunbar, 2004).

Recent research has begun to examine some of the factors that influence the relations between causal beliefs and empirical evidence (see Garcia-Retamero, Hoffrage, Müller, & Maldonado, 2010 for a review). In a decision-making task by Garcia-Retamero, Wallin, and Dieckmann (2007), participants with access to causal information became more frugal, more accurate, and more precise in estimating the predictive power of the cues. Furthermore, Garcia-Retamero et al. (2009) examined the potentially differential influence of causal beliefs on decision making (e.g., smoking a cigarette) versus judgments (e.g., knowing cigarettes cause cancer) in a dual forced-choice task. These authors demonstrated that people use causal information as an anchor for decisions and causal judgments. In their study, selected groups received pre-training with either causal or neutral cues. After pre-training, participants underwent a decision task with causal and neutral cues that differed in validity information. Results revealed that participants, on average, based their decisions mainly on the empirical evidence (i.e., cue validities), and, to a lesser extent, on the causal information. Causal judgments, however, were only based on the empirical evidence when participants had received pre-training without any causal information, or in the absence of causal information. When participants received causal pre-training or causal cues in the decision task, they based their judgments primarily on the causal information or on causal information with high validity (additive effect). Results suggest that the interplay between decisions and judgments is relatively poorly understood.

The present research aims to extend our understanding of the dynamic interplay of causal beliefs, decision making, and causal judgments. We hypothesized that participants could improve their assessment of the empirical evidence in decision making with greater experience and the availability of cues that varied widely in their predictive accuracy (see also Hogarth & Karelaia, 2007). We further aimed to map factors that may explain the disassociation between judgments and decisions. Previous research documented different inferences for choice, namely observations and interventions (Hagmayer & Sloman, 2009; Meder et al., 2009), and demonstrated that causal relations are especially relevant for the latter ones. Consequently, causal information might also impact decisions differently than judgments. In two experiments, we first tested the robustness of previous findings (Garcia-Retamero et al., 2009), refining manipulations of the presented empirical evidence. We then improved decision accuracy by identifying key factors (e.g., causal information, cue validities, amount of experience).

Experiment 1

Previous research illustrated that causal beliefs influence decisions and causal judgments when high and low valid cues predict an outcome (Garcia-Retamero et al., 2009). However, these findings did not indicate whether a narrow difference between cue validities would result in a preference for high valid cues (over low valid cues) when no causal information or pre-training is provided. Accordingly, we extended the previous research by applying two further manipulations. First, we added an experimental group that did not receive any pre-training or causal information. Second, we decreased the difference between cue validities to facilitate the detection of highly diagnostic cues – this was an important step as previous findings did not indicate whether participants would rely on the empirical evidence under this condition.

To manipulate previous experience, we provided pre-training to selected groups (either causal or neutral) and hypothesized (H1) that participants would rely on this experience to evaluate the evidence presented in the task. We further hypothesized (H2) that a lack of causal anchors and experience would facilitate the detection of empirical evidence (see also Catena, Maldonado, Perales, & Cándido, 2008; Fugelsang & Thompson, 2003). Lastly, we hypothesized (H3) that people without any previous experience would rely on their causal beliefs to a greater extent than on empirical evidence.

Method

Participants. **S**ixty-four students (52 women, M = 21 years, range 18–32) from the University of Granada participated for course credit. Participants were randomly assigned to one of the four equally sized groups (n = 16). In all experiments, the computerized task was conducted individually and lasted approximately 1 hr.

Procedure. Participants were first instructed to choose between two patients (displayed column-wise) and select the one who would show a higher degree of allergic dermatitis (see Figure 1). Four selectable cues described the two patients. Participants had to view at least one cue to make a decision. The cues revealed information about whether the two patients used a certain shower gel, ingested a prescription drug, were bitten by an insect, or worked in a certain industry (see Appendix). The order of the four cues – presented as information-boxes (see also Bröder, 2003; Garcia-Retamero et al., 2007, for similar procedures) – was fixed for each participant, but varied randomly between participants. Whenever an information-box was selected, the information appeared simultaneously for both patients on the screen and remained visible until a decision was made (see Dhami & Harries, 2009 for a similar procedure; Ford, Schmitt, Schechtman, Hults, & Doherty, 1989).

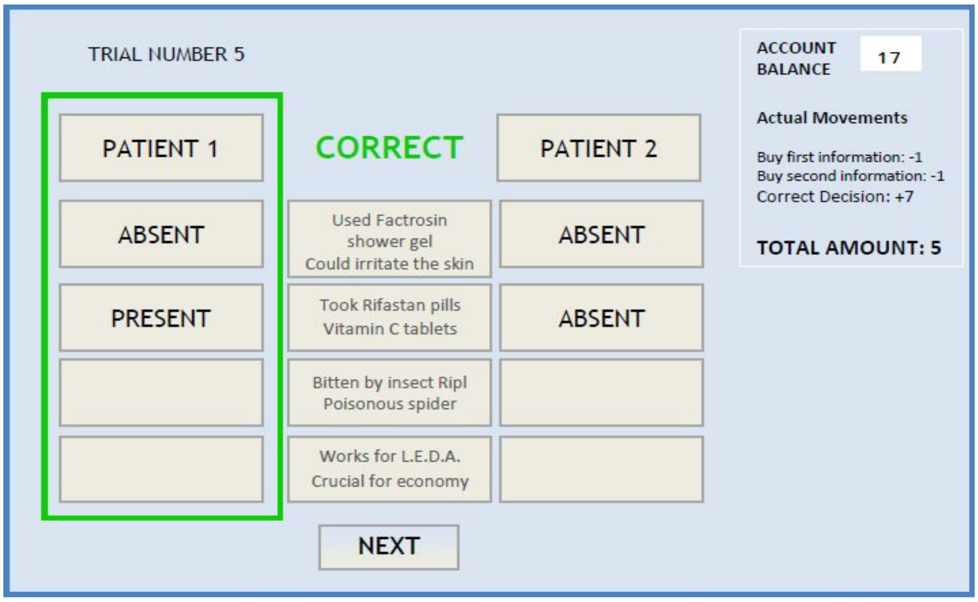

Figure 1. Screenshot: First, the participant searched for the cue ‘‘use of a shower gel.’’ This cue did not discriminate between the patients. Next, the participant searched ‘‘ingestion of a prescription drug.’’ This cue revealed a negative value for patient 1 and a positive value for patient 2. Examination of cues carried a total cost of 2 points. The participant decided patient 2 would show a higher degree of dermatitis. This correct decision yielded 5 points total.

After completing the cue-search, participants made a decision (i.e., selected a patient) by clicking a button. Subsequent feedback about the correctness of the decision was displayed. Participants made 60 decisions with no time constraints (divided into three blocks of 20 trials). Each participant received the same set of trials within each block in random order. An account was always visible on the computer screen and participants were told to attain the maximum points. For each inspected cue, 1 point was deducted from overall payoffs. Participants could gain 7 points for each correct decision. To gain many points during the task, participants had to detect highly predictive cues and avoid exhaustive search.

Following 60 decisions, participants were asked to what extent (from _10 to 10) each of the four cues was a reliable cause predicting the outcome (higher degree of dermatitis). This question was related to the accumulated experience of task feedback. A positive rating implied the cue caused the outcome; a negative rating represented a cue that prevented the outcome. A zero rating implied that the cue did not have an effect. Before the decision phase of the experiment, some participants underwent a pre-training phase where they also made 60 decisions.

Design. To analyze the influence of causal beliefs, we instructed participants that two of the four cues were causally linked to the outcome (causal cues). Instructions for the remaining two cues did not provide any causal link to the outcome (neutral cues). For instance, the cue "patients ingested a certain prescription drug" (Rifastan pills) could have either a causal ("an antibiotic, which could lead to skin swelling") or a neutral version ("vitamin C tablets, which are crucial for sight"). A pretest confirmed that causal – in contrast to neutral – cues were perceived to have a strong causal power (Appendix).

To measure the impact of the empirical evidence, we manipulated cue validities within-subjects. The ***validity*** of a cue is the probability that this cue leads to a correct decision, given that it discriminates between the alternatives (i.e., the cue is present in one of the patients and absent in the other; Gigerenzer, Todd, & the ABC Research Group, 1999).[7] More precisely, cue validity above 0.5 would predict the outcome (i.e., a

[7] It is important to differentiate between the manipulation of the cue validity and contingency. The contingency between a candidate cause (***c***, cue) and its effect (outcome, ***o***) is defined by $\Delta \boldsymbol{P}_c = \boldsymbol{P}(o|\boldsymbol{c}) - \boldsymbol{P}(o|\boldsymbol{c})$, where $\boldsymbol{P}(o|\boldsymbol{c})$ is the probability of o given the presence of ***c*** (i.e., validity of the cue) and $\boldsymbol{P}(o|\boldsymbol{c})$ is that probability given the absence of ***c***. In contingency terms, a positive $\Delta \boldsymbol{P}_c$ value refers to ***c*** as a generative or excitatory cause; a negative $\Delta \boldsymbol{P}_c$ value refers to c as a preventive or inhibitory cause; a ***c*** value around 0 means that cue and outcomes are unrelated (Lien & Cheng, 2000). To meet the

generative cause); cue validity set below 0.5 and above 0.0 would predict the absence of the outcome or no relation to the outcome. In the decision phase of the experiment, two of the four available cues (one causal and one neutral cue) had high validity (i.e., 0.90); the remaining two cues (the remaining causal and neutral cue) had low validity (i.e., 0.60). In all experiments, the mean discrimination rate of the four cues was 0.59 (which ranged from 0.55 to 0.60) and inter-cue correlation was close to 0. The discrimination rate of a cue is the number of pair comparisons in which the cue is present in one alternative and absent in the other.

There were four conditions in the experiment. Participants in the causal control group could inspect four different cues to make a decision: a causal high- (CH), a causal low- (CL), a neutral high- (NH), and a neutral low- (NL) validity cue. Participants in a second control group (the neutral control group) did not receive any causal instruction and could base their decisions and causal judgments on only four neutral cues (two high- and two low-validity cues). This group represented the baseline measuring the net influence of allocated validities or experienced evidence.

Finally, we provided pre-training for two experimental groups to analyze the effect of previously experienced evidence. Participants in the pre-causal group underwent pre-training with only causal high- and causal low-validity cues (CH, CL); pre-training for the pre-neutral group contained only neutral high- and neutral low-validity cues (NH, NL). During pre-training, cue values for each patient were displayed automatically – no cue-search was required. Both groups were asked to make 60 decisions and outcome feedback was provided. After pre-training, these two groups

requirements for a decision task following Gigerenzer et al. (1999), we applied a manipulation of validity. To meet our interest in causal judgments, we also calculated the contingency values for each cue after the experiment. High valid cues (i.e., 0.90) resulted in a contingency between 0.50 and 0.60; low valid cues (i.e., 0.60 or 0.10) resulted in a contingency between 0.30 to 0.40 and −0.20 to 0.00 (mean contingency −0.10 reassuring that the cue had no relation to the outcome), respectively.

could base their decisions and causal judgments – similarly to the causal control group – on four different cues (Table 1).

Results and Discussion

All analyses contain two main sections. First, we report findings of decision making in the task. Secondly, we present results of subsequent causality judgments. Following Garcia-Retamero et al. (2009), post hoc comparisons were all conducted with Fisher (LSD), alpha-level .05. In Experiment 1, we conducted 4 (group: ***pre-causal, pre-neutral, causal control, neutral control***) × 4 (within-subjects cues) analyses of variance (ANOVAs).

Tabla 3. Experimental procedure in Experiment 1 and 2

Groups in Experiment 1	Instruction	Pre-Training	Instruction	Decision Task
Causal control group	–	--	Causal	CH, CL, NH, NL
Pre-causal group	Causal	CH. CL	Causal	CH, CL, NH, NL
Pre-neutral group	Neutral	NH. NL	Causal	CH, CL, NH, NL
Neutral control group	–	--	Neutral	NH, NL, NH, NL
Groups in Experiment 2	Instruction	High Validity	Low Validity	Decision Task
Causal 9/6	Causal	0.90	0.60	CH, CL, NH, NL
Causal 9/1	Causal	0.90	0.10	CH, CL, NH, NL
Neutral 9/6	Neutral	0.90	0.60	CH, CL, NH, NL
Neutral 9/1	Neutral	0.90	0.10	NH, NL, NH, NL

Note: CH and CL refer to causal high- (0.90, in both Experiments) and causal low-validity cues (only 0.60 in Experiment 1 and 0.60/0.10 in Experiment 2); NH and NL refer to neutral high- and neutral low-validity cues.

Decision Making. Decision making measured the proportion of trials in which participants decided in favor of a specific cue. The ANOVA showed a significant main effect of cue, $F(3, 180) = 9.50$, $MSE = 601.58$, $p < .001$, $\eta_p^2 = .14$, and an interaction between group and cue, $F(9, 180) = 2.25$, $MSE = 601.58$, $p = .021$, $\eta_p^2 = .10$.

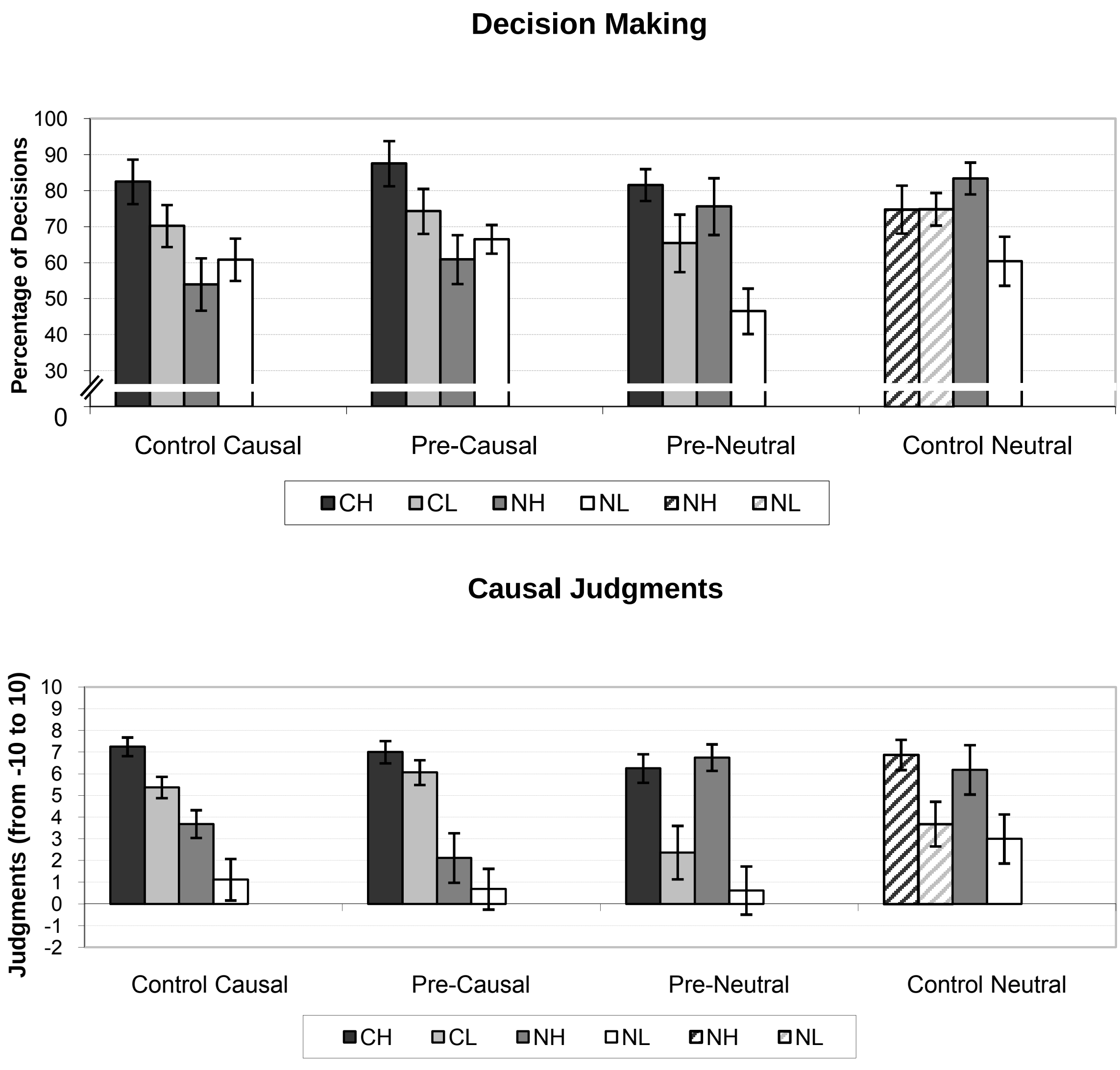

Figure 2. Percentage of trials in which participants decided in favor of each cue and causal judgments about each cue (CH, CL, NH, NL) in Experiment 1. The ***control neutral group*** could base decisions and judgments on four neutral cues only (NH. NL, NH, NL). Error bars represent one standard error.

Post hoc comparisons revealed that previous beliefs and empirical evidence were influencing decisions in the ***pre-causal*** and ***causal control group*** – participants favored the causal high-validity cue more often than the causal low-validity cue and all neutral cues, independently of cue validity (see Figure 2). ***Pre-neutral group*** participants decided more often in favor of both high-validity cues and the causal low-validity cue than the neutral low-validity cue. Finally, members in the ***neutral control group*** favored all cues over one low-validity cue.[8]

Causal Judgments. The ANOVA on causal judgments showed a significant effect of cue, $\boldsymbol{F}(3, 180) = 33.17$, $\boldsymbol{MSE} = 9.82$, $\boldsymbol{p} < .001$, $\eta_p^2 = .36$, and a significant interaction between group and cue, $\boldsymbol{F}(9, 180) = 4.39$, $\boldsymbol{MSE} = 9.82$, $\boldsymbol{p} < .001$, $\eta_p^2 = .18$.

Participants in both the ***causal control*** and the ***pre-causal group*** perceived both causal cues as more reliable predictors of the outcome than neutral cues, independent of cue validity (Figure 2). Participants in the ***causal control group*** additionally perceived the neutral high-validity cue as more reliable than the neutral low-validity cue, which shows that validity information also affected decisions. Participants in the ***pre-neutral*** and ***neutral control group*** evaluated high-validity cues as more reliable predictors for the outcome than low-validity cues (independent of causal relation).

In Experiment 1, decisions and judgments in the causal control and the ***pre-causal group*** were influenced by participants' causal beliefs and – to a lesser extent – by the validity of the cues (H1; H3). Participants in the ***pre-neutral group*** were influenced by pre-training (H1) with neutral cues and mainly used the validity information as an anchor classifying the new evidence. Similarly, participants in the

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[8] Participants might have held some a priori belief that causally linked the second cue (NL2 = ''patient ingested Rifastan pills'') to the outcome (allergic dermatitis) independent of its low validity.

neutral control group, who lacked causal anchors (H2), preferred high-validity cues in judgments and decisions. Overall, participants were able to adapt to the empirical evidence when neither causal information nor pre-training was provided. Next, we sought to examine the robustness of causal beliefs and to map some key factors underlying the interplay between decisions and judgments.

Experiment 2

Experiment 1 demonstrated that pre-training significantly affected participants' decision-making processes and showed some dissociation between participants' decisions and judgments. Here, we attempted to overcome participants' neglect of empirical evidence, identifying mechanisms underlying decision making. Accordingly, we enhanced people's experience with the empirical information in the decision task by increasing the amount of trials. To examine the sensitivity to the empirical evidence, we manipulated the differences between cue validities (i.e., wide vs. narrow).

Method

Participants. Ninety-four students (76 women and 18 men, mean age 22 years, range 19–47) from the University of Granada participated. Participants were randomly assigned to one of the two equally sized groups (n = 23 vs. n = 24), who received either wide versus narrow differences between cue validities, respectively.

Procedure and Design. Experiment 2 exactly followed Experiment 1, except that:

(1) We increased the amount of trials and participants made 120 decisions (divided into two blocks of 60 trials).

(2) High- and low-validity cues differed either to a narrow or wide extent (i.e., 0.60 for low valid or 0.10 for highly low valid cues and 0.90 for all high-validity

cues, respectively). Note that low-validity cues of 0.10 would correspond to a contingency between 0.00 and _0.20 (i.e., ***preventive*** cues), whereas high-validity cues would correspond to a contingency between 0.60 and 0.70 (i.e., ***generative*** cues).[1]

(3) No pre-training was provided.

In the following, we will speak of the experimental groups as the ***Caus9/1***, ***Caus9/6***, ***Neut9/1***, and the ***Neut9/6 group*** (see Table 1).

Following Experiment 1, we expected that causal groups would “learn” to rely on the empirical information with more trials (enhanced task experience), independent of causal relations (H1). We anticipated this result specifically when the manipulated difference between high- and low-validity cues was wide (i.e., ***Caus9/1***) versus narrow (i.e., ***Caus9/6***) (H2). Both neutral groups were expected to primarily focus on the high-validity cues and served as control groups for the causal manipulation (H3).

Results and Discussion

Decision Making. We conducted a 4 (group: ***Caus9/1, Caus9/6, Neut9/1, Neut9/6***) × 4 (within-subjects cues) × 2 (blocks of 60 decisions) mixed ANOVA on the dependent variable decision making. The ANOVA showed a significant main effect of cue, $\boldsymbol{F}(3, 258) = 23.40$, $\boldsymbol{MSE} = 1{,}428.86$, $\boldsymbol{p} < .001$, $\eta_p^2 = .21$, and an interaction between group and cue, $\boldsymbol{F}(9, 258) = 2.11$, $\boldsymbol{MSE} = 1{,}428.86$, p = .029, $\eta_p^2 = .07$, indicating that participants in each group decided for different cues throughout the task. There was also an effect of block, $\boldsymbol{F}(1, 86) = 47.61$, $\boldsymbol{MSE} = 618.67$, $\boldsymbol{p} < .001$, $\eta_p^2 = .36$, and an interaction between group and block, $\boldsymbol{F}(3, 86) = 4.48$, $\boldsymbol{MSE} = 618.67$, $\boldsymbol{p} = .006$, $\eta_p^2 = .14$, which referred to differences among groups in the preference for cues between decision blocks. Finally, the analysis indicated a significant interaction between cue, block, and group, $F(9, 258) = 2.20$, $MSE = 666.55$, $p = .022$, $\eta_p^2 = .07$.

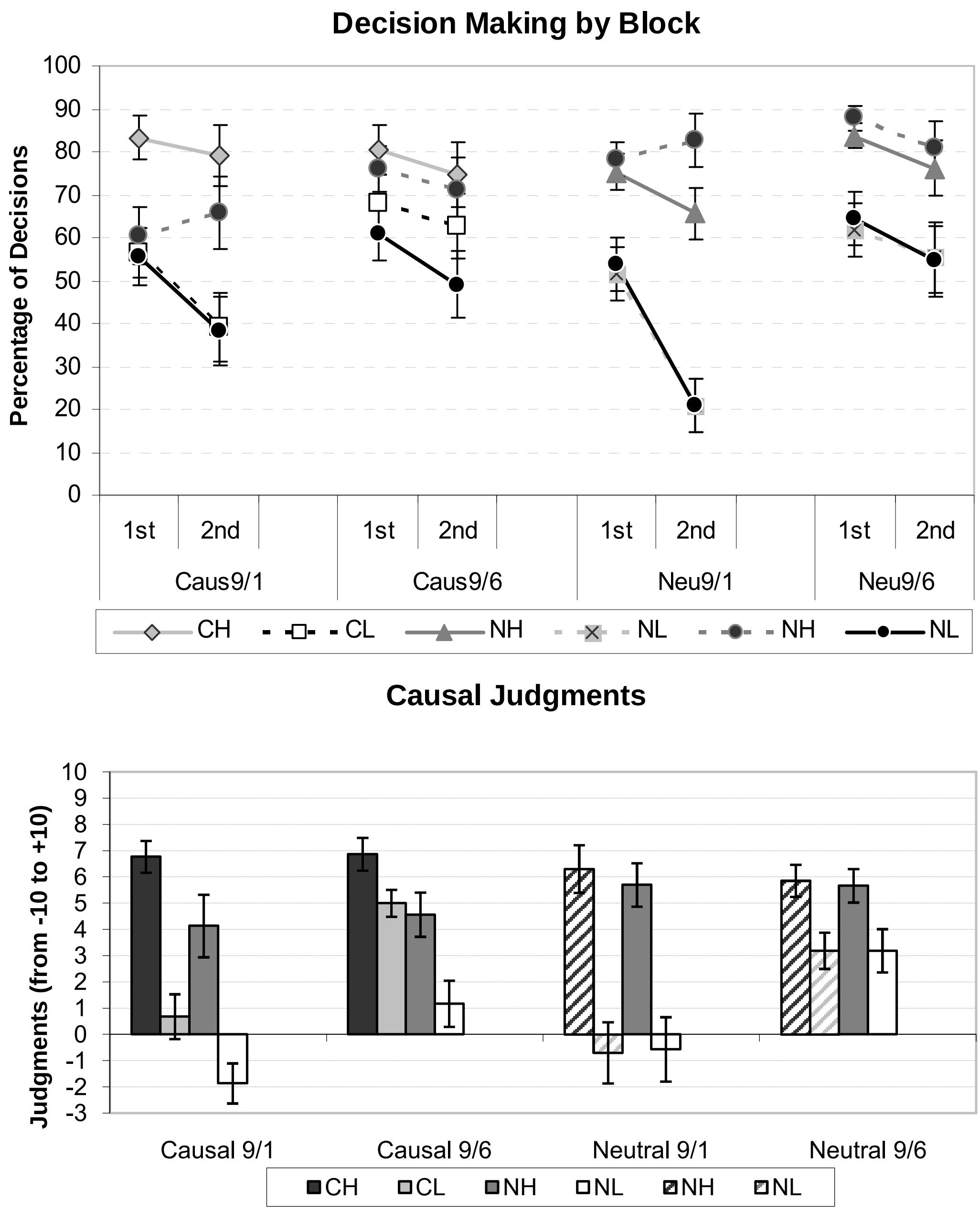

Figure 3. Percentage of trials in which participants decided in favor of each cue and causal judgments about each cue within two blocks of the decision phase and causal judgments about each cue (CH, CL, NH, NL) in Experiment 2. The ***Neut9/6*** and ***Neut9/1*** group could base their decisions and judgments on four neutral cues only (NH. NL, NH, NL). Error bars represent one standard error.

Post hoc tests revealed that participants in the ***Caus9/1*** group preferred the causal high-validity cue in the first block of trials (Figure 3) and decided in favor of both high-validity cues in the second trial block. These participants stuck to highly valid causal beliefs at the beginning of the task, but learned to integrate and rely on the empirical evidence with increased task experience..

Interestingly, participants' use of low valid cues only decreased below the 50% line after the second trial block. Members in the ***Caus9/6*** showed a preference for both causal cues and the neutral high-validity cue in the first trial block, but decisions in favor of the neutral low-validity cue decreased below the 50% line in the subsequent trials. Participants in this group stuck to their causal beliefs throughout the task and had difficulties differentiating between cues. Both neutral groups preferred high-validity cues throughout the two blocks of trials (Figure 3).[9] Decision makers might have inferred a causal relation for highly valid neutral cues, as they did not differentiate between causally related and high valid cues

Causal Judgments. We conducted a 4 (group: ***Caus9/1, Caus9/6, Neut9/1, Neut9/6***) × 4 (within-subjects cues) mixed ANOVA on the dependent variable causal judgments. The ANOVA yielded a significant effect of cue, $F(3, 255) = 40.78$, $MSE = 16.14$, $p < .001$, $\eta_p^2 = .39$, and a significant interaction between group and cue, $F(9, 255) = 3.38$, $MSE = 16.14$, $p < .001$, $\eta_p^2 = .11$.

Members of all groups, except the ***Caus9/6*** group, judged the high-validity cues as most reliable predictors for the outcome (Figure 3). Judgments of the ***control neutral groups*** mainly reflect the contingency values derived from cue validities and accentuate the effect of causal beliefs in the experimental ***causal groups***. Participants in the ***Caus9/1*** group relied more on the causal than the neutral cues (causal high > neutral high; causal low > neutral low) indicating an additive effect of causality and validity.

[9] In the Neut9/1 group, the preference for one neutral high-valid cue during the second block could have been due to the surplus of points when selecting fewer cues.

Similarly, the ***Caus9/6*** group primarily relied on the causal high-validity cue and evaluated low causality and high validity equally. Finally, the evaluation of low-validity neutral cues in both the ***Caus9/1*** and the ***Neut9/1*** group showed a contrast effect (inverse relationship to the outcome).

In decision making, participants in the ***causal groups*** were able to rely on the empirical information (regardless of the causal relation) with greater task experience (H1), but only when validities differed to a wide extent (H2). When participants received only neutral cues (H3), they favored high-validity cues throughout the two blocks of trials to make decisions. These results resemble the underlying cue validities. In causal judgments, all experimental groups – except the ***Caus9/6*** group – preferred high-validity cues (H1; H2). We suggest that the narrow difference between high- and low-validity cues in the ***Caus9/6*** group supported their consideration of causal cues more in both judgments and decisions. Interestingly, these results correspond to the contingencies underlying the cue validities.

General Discussion

Results demonstrate that causal beliefs can influence both decisions and causal judgments in a two-alternative forced-choice medical decision task. Participants used instructions or pre-training (***causal*** vs. ***neutral***) as an anchor to make decisions and causal judgments. This anchor, however, did not remain stable when participants accumulated more experience: By increasing the number of trials and distinctness of the validity information, people improved their integration of empirical evidence in decision making and judgments. In line with predictions, causal beliefs helped participants focus on a subset of specific cues, which led to better diagnostic performance. In addition, decision makers became faster in learning the validity of causal versus neutral cues, although both cues had similar predictive values. However, participants had some difficulties integrating low-validity cues when the underlying cue-outcome relationship was intended to be causal. The current experiments document factors that enable people to integrate empirical evidence and overcome neglect of causal information in a medical diagnostic task.

Our findings provide at least three interesting theoretical implications. First, results provide converging data highlighting the utility of a two mechanism-based model for explaining decision making, causal reasoning, and causal learning (Catena et al., 2008; Fugelsang & Thompson, 2003; Lien & Cheng, 2000). Especially when validities differed to a wide extent (Experiment 2), people integrated highly valid information with their causal beliefs. Alternatively, these results could also be considered from a Bayesian point of view (Griffiths & Tenenbaum, 2005). In their support model, Griffith and Tenenbaum (2005) act on the assumption that a causal judgment reflects the reasoner's degree of certainty linking cause and effect. The existence of four causal candidates in our experiments would result in 16 possible models – excluding background causes and the possibility of a priori likelihoods of these models. Although it may be possible, Bayesian models have not yet been developed to handle this level of complexity.

Secondly, our findings highlight potential differentiations between decision making and causal judgments, which are often treated as interchangeable. We found that results for decisions reflected the manipulation of the validity, whereas causal judgments reflected the underlying contingency values. Causal information, however, had an additive effect on both processes. We suggest that decisions had been used as hypotheses that were adjusted by the outcome whereas judgments reflected inferences of the net causal relation.

Third, participants could only improve their task performance when focusing on a specific set of highly predictive cues. An exhaustive information search might have led to better diagnostic performance (Hogarth & Karelaia, 2007), but was restricted by the account setting. Consequently, the decision task supported a guessing strategy focusing on causal information first and on cue validity (via learning) in a second step. This experimental setting would not be applicable for analyzing elaborative searching strategies.

Although we were able to show how people can integrate the empirical information within the experimental setting of a two-alternative forced-choice task, further research is needed trying to replicate these findings in natural settings (e.g., physician treatment choices). Similarly, this research could be extended to map the strength of causal beliefs in different domains or ecologies (Gigerenzer & Brighton, 2009). Furthermore, the importance of individual differences should not be underestimated. Participants' differences in abilities (e.g., working-memory-capacity) might predict decision strategies when encoding the empirical evidence (Cokely & Kelly, 2009; Cokely, Kelley, & Gilchrist, 2006) and may influence differences between decisions and judgments. Finally, we hypothesize that causal judgments resulted from one's experience with previous decisions and act as an anchor for future decisions. We are currently examining these issues in our laboratories.

Conclusion

People are more likely to consider information that confirms their initial assumptions – and neither scientists nor health professionals are immune to this bias (Fugelsang et al., 2004; Haynes, 2009). The current research highlights the impact of causal beliefs when interpreting new data. Here, we documented (1) some dissociation between decisions and judgments and (2) that even when participants held strong causal beliefs greater task experience and higher cue discriminability enabled them to adjust these beliefs to the environment. Results provide new converging evidence on how causal beliefs can undergo a revision and how such beliefs can be updated with empirical information.

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Appendix 1

Cue	*Causal version*	*Neutral version*
Some patients used Factrosin shower gel,	made of Peruvian balm, which could irritate the skin	Having a soothing fragrance, which is very pleasant
Some patients ingested Rifastan pills,	An antibiotic, which could lead to skin swelling	Vitamin C tablets, which are crucial for sight
Some patients were bitten by the insect Ripl,	A poisonous spider	A regular blue and white butterfly
Some patients work in the industry L.E.D.A.,	Producing abrasive products to clean toilets	Which is crucial for the economy of the city

Note: Material used in the Experiment: Causal and neutral versions of four properties that participants could use to determine which of two patients would show a higher degree of allergic dermatitis.

Independent naïve participants (n = 160) rated the extent that causal or neutral cues cause the outcome on a scale from 100 (highest positive relationship) to 0 (no relationship). Causal cues were judged to have a stronger causal impact on the outcome (mean rating = 58.5) than neutral cues (mean rating = 24.7, $F(1, 78) = 124.5$, $p<.001$). There was no difference in the perceived strength of the relatedness with the outcome among causal or neutral cues, $F(3, 117) = 1.7$, $p=.17$; $F(3, 117) = 2.37$, $p=.17$, respectively.

CHAPTER 3

The Impact of Domain-Specific Beliefs on Decisions and Causal Judgments[10]

Abstract

Extensive evidence suggests that people often rely on their causal beliefs in their decisions and causal judgments. To date, however, there is a dearth of research comparing the impact of causal beliefs in different domains. We conducted three experiments to map the influence of domain-specific causal beliefs on the evaluation of empirical evidence when making decisions and subsequent causal judgments. Participants made 120 decisions in a prognostic task, which was framed in either a medical or a financial context. Before each decision, participants could actively search for information about the outcome ("occurrence of a disease" or "decrease in a company's share price"), available in four cues. To analyze the strength of causal beliefs, we set two cues to have a generative relation to the outcome and two to have a preventive relation to the outcome. To examine the influence of empirical evidence, we manipulated the predictive power (i.e., cue validities) of the cues. All experiments included a validity switch, where the four selectable cues switched from high to low validity or vice versa. Participants had to make a causal judgment about each cue before and after the validity switch. In the medical domain, participants stuck to their causal beliefs in causal judgments, even when evidence was contradictory, while decisions showed an effect of both empirical and causal information. In contrast, in the financial domain, participants mainly adapted their decisions and judgments to the empirical evidence. We conclude that (1) the strength of causal beliefs is shaped by the domain, and (2) domain has a differential influence on the degree to which empirical evidence is taken into account in causal judgments and decision making.

[10] Submitted as: **Müller, S. M.**, Garcia-Retamero, R., Galesic, M. & Maldonado, M. (submitted). The impact of domain specific beliefs on decisions and causal judgments. ***Journal of Experimental Psychology: Applied.***

Introduction

In a wide range of domains, people encounter problems that require adaptive, content-specific solutions. For example, decisions about medical treatments might differ substantially from those about financial investments, as the structure of problems and the nature of consequences are different (Garcia-Retamero & Galesic, 2011). Decisions in different domains can promote content-specific rules for information processing. Prominent examples are the cheater-detection mechanism in the domain of social exchange (Cosmides & Tooby, 1989, 1992; Gigerenzer & Hug, 1992), the selection of mating partners (Buss, 1992), adaptive memory for objects relevant for survival (Nairne, Thompson, & Pandeirada, 2007), and the prediction of other people's behavior (Baron-Cohen, 1995). We propose that domain-specific information processing may affect the extent to which people use their causal beliefs when making judgments and decisions. We focus on two life domains that differ in their typical structure of problems and nature of consequences: the medical and the financial domain. In fact, it has been shown that people are more willing to take advice in the medical domain than in the financial domain (Garcia-Retamero & Galesic, 2011). Would these two domains also differ in the way causal beliefs affect judgments and decisions?

Domain-Specific Causal Beliefs

Two dimensions may influence the way information is processed in a particular domain: (1) the ***temporal variability of cue validities***, and (2) whether decisions could have ***life-threatening consequences***. We refer to the validity of a cue as the probability that it leads to a correct decision, given that it discriminates between the alternatives (Gigerenzer, Todd, & the ABC Research Group, 1999). The temporal variability of cue validities can be perceived on a continuum ranging from low to high. Low temporal variability means that the cue validities show little or no change over time. In this case, the reliance on causal beliefs might be of great benefit to the decision maker, as cues are very likely to remain valid over time. For example, in the health domain, a substance or behavior that was noxious years ago is likely to be still noxious today, because essential physiological processes within the human organism are very unlikely to change over such periods of time. Indeed, people have been shown to persist in very strong causal beliefs in the medical domain, even when contradictory evidence is available (Beyerstein, 1997; Haynes, 2009). In contrast, high temporal variability of cue validities means that there is uncertainty about cue validity at any given moment. Relying on past causal beliefs about these cues carries the risk of using outdated information and making wrong decisions. An example from the financial domain may illustrate this idea: To maximize profit in the financial market, we cannot rely on one specific outcome of a cue but must deal with a distribution of potential outcomes that may change over time. Consequently, the validity of a cue may not appear very reliable over time—for instance, even the long-term survival of a company cannot predict its survival in the future (Alchian, 1950). People, therefore, might be more willing to continually update their causal beliefs to reflect the current market situation (Munier, 1991).

Life-threatening consequences of decision outcomes may be another factor influencing domain-specific information processing: Outcomes within the health domain are more likely to carry life-threatening consequences than those in other domains (Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2008). Changing causal beliefs in the health domain might therefore be potentially deadly. In contrast, changing causal beliefs in the financial domain might affect one's economic status but would rarely lead to death. Consequently, it is more likely that people update and revise their causal beliefs about money than about health. To the best of our knowledge, research has not addressed this point to date.

Causal Beliefs in Decision Making and Causal Judgments

Previous research has shown that people cannot and do not fully process all available information in the environment (Simon, 1990). To improve decision making, information search can be limited by focusing on the most relevant cues (Garcia-Retamero, Wallin, & Dieckmann, 2007; Gigerenzer & Brighton, 2009). In this way, decision making becomes fast—because less computation is needed—and frugal, because only certain information is considered (Gigerenzer, 2008).

One way people select and structure the information in their environment is to apply mental models about cause-and-effect relationships to identify the most relevant cues (Garcia-Retamero, Hoffrage, & Dieckmann, 2007; Tversky & Kahnemann, 1974; Waldmann & Hagmayer, 2001; Waldmann, Hagmayer, & Blaisdell, 2006). Causal beliefs or prior experience can thereby boost fast and frugal decision making (Garcia-Retamero, Wallin, et al., 2007). For instance, an experience with a poisonous substance is likely to keep an agent away from the substance in the future in a wide range of species (Garcia & Koelling, 1966). Therefore, inferences about causal relations often frame decisions and can be considered as hypotheses that are tested and updated with new evidence (Koslowski, 1996).

However, causal beliefs can also interfere with the accurate evaluation of new empirical evidence resulting in a neglect of contradictory information: Even scientists and clinicians have been shown to disregard findings that are not in line with their previous assumptions (Fugelsang, Stein, Green, & Dunbar, 2004; Haynes, 2009). Research confirming the reliance on causal beliefs and neglect of empirical evidence showed that this effect is larger in causal judgments than in decision making (Garcia-Retamero, Müller, Catena, & Maldonado, 2009). Although in one study participants increased their reliance on the empirical evidence (cue validities) when provided with pre-training on neutral cues, greater amounts of empirical evidence, or highly discriminative cues, studies have also found some dissociation between causal judgments and decision making (Fugelsang et al., 2004; Müller, Garcia-Retamero, Cokely, & Maldonado, in press).

Accumulating research suggests that the influence of causal beliefs and empirical evidence in causal judgments and decision making is not straightforward and that the interplay between decisions and causal judgments is still relatively poorly understood (Griffiths & Tennenbaum, 2005; Meder, Hagmayer, & Waldmann, 2009; Sloman & Hagmayer, 2006; see Garcia-Retamero, Hoffrage, Müller, & Maldonado, 2010, for a review). In the present studies we sought to extend previous research by comparing the impact of causal beliefs and empirical evidence in two different domains (medical and financial), thereby mapping the dissociation between causal judgments and decision making.

Experiment 1

To investigate the effect of domain-specific beliefs, we compared causal judgments and decision making in two different domains: financial and medical. Participants had to select which of two alternatives led to a higher outcome value, using four available cues (reflecting either the "behavior of a patient" or the "performance of a company"). To investigate the effect of causal beliefs, instructions revealed whether cues had either a generative ("may cause") or a preventive ("may not cause") relation with the outcome ("disease X" or "a share price decrease"). To map the influence of empirical evidence, we introduced a "cue validity switch": Cues that were highly valid at the beginning of the decision task changed to low validity after a certain number of trials and vice versa. Participants were not instructed about the validity switch.

To avoid any bias of participant's previous causal knowledge, we presented cues that lacked any specific information about the domain (and labeled cues only as Cue A, B, C, and D). This enabled us to investigate whether domain-specific background information about the task learned through the instructions (in either domain) would lead to differences in decisions and causal judgments even with completely abstract cues.

We had three hypotheses: First, we hypothesized that the effect of causal beliefs would be stronger in the medical than in the financial domain. We expected this finding despite there being a lack of any domain-specific information about the cues during the decision task. People might perceive that decisions about health have more crucial, life-threatening consequences than those about money; they also might perceive cue validities as stable over time in the medical domain but as rather variable in the financial domain. Second, following the previous assumptions, we hypothesized that participants would be more likely to adapt to empirical evidence (i.e., cue validities) in the financial than in the medical domain. Finally, in line with our recent research documenting a dissociation between decisions and causal judgments (i.e., Müller et al., in press), we further hypothesized that the impact of causal beliefs would be stronger in causal judgments than in decision making.

Method

Participants. Thirty-two students (19 women and 13 men, average age of 25 years, range 19–32 years) from the Free University Berlin, Germany, participated in the experiment for monetary compensation. Participants were randomly assigned to one of two equally sized groups (***n*** = 16).

Procedure. First, participants were instructed to choose between two alternatives (displayed column-wise) and select the one with the higher outcome value (i.e., a decision task). Participants in the medical group had to choose between two patients and select the one "who would be more likely to get disease X." Participants in the financial group had to choose between two companies and select the one "that would be more likely to experience a decrease in their share price" (see Figure 1, top). Four selectable cues—presented as boxes on the screen—described the two alternatives (patients or companies); to see the values for a particular cue, participants had to click on the respective box. In both groups, participants had to search for at least one cue to make a decision. The order of the four cues was fixed for each participant but varied randomly between participants (see also Bröder, 2000, 2003; Garcia-Retamero, Wallin, et al., 2007, for similar experimental procedures).

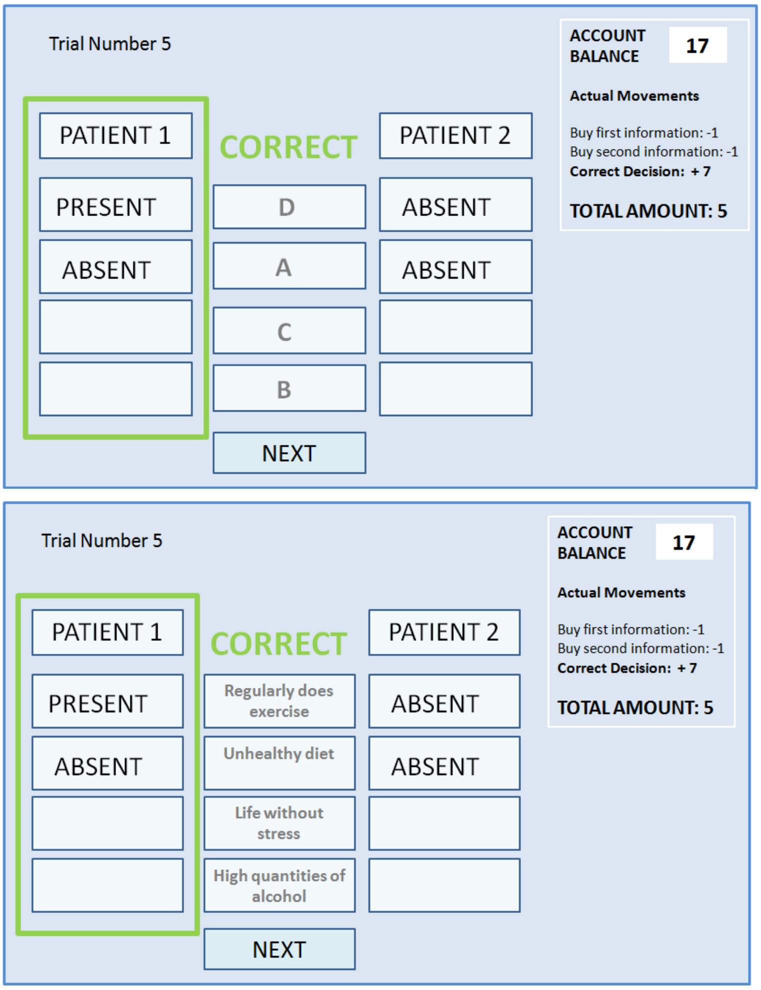

Figure 1. Top: Screenshot of the experimental task in Experiment 1. Bottom: Screenshot of the experimental task in Experiments 2 and 3. In the bottom example, the participant began information search with the cue describing whether the patients were maintaining an "unhealthy diet." This cue uncovered a negative value for Patient 1 and a positive value for Patient 2. The participant next searched whether the patients were "regularly exercising." This cue did not discriminate between the two patients, as neither of them was exercising regularly. Two points have been subtracted from her account for looking up these two cues. The participant decided that Patient 2 would be more likely to develop heart disease—a correct decision that led to a gain of 5 points in this trial.

Whenever a box was selected to retrieve information about the value of a cue, the information on whether the cue was absent or present appeared simultaneously for both alternatives on the screen and remained visible until a decision was made (see also Ford, Schmitt, Schlechtman, Hults, & Doherty, 1986).

After completing the cue search, participants made a decision by clicking on a button (i.e., selecting one of the two patients or companies), and subsequent feedback about the correctness of the decision was displayed. Participants made 120 decisions with no time constraints—divided into two blocks of 60 trials. Each participant received the same set of trials within each block and in random order. An account was always visible on the computer screen and participants were told to attain the maximum points, which corresponded to a monetary payoff. For each cue looked up, 1 point was deducted from the overall total; participants could gain 7 points for each correct decision.

Design. To analyze the influence of causal beliefs, we told participants at the beginning of the experiment via instruction that two of the four cues generated the outcome (***generative cues***) and the remaining two cues prevented the outcome (***preventive cues***). In both the medical and the financial domain, cues were labeled A, B, C, and D. Each cue had a preventive version (may prevent the disease/may prevent a decrease in share price) and a generative version (may cause the disease/may cause a decrease in share price). Whether cues had a preventive or generative version was randomized across participants (see also Figure 1, top).

To measure the sensitivity to empirical evidence, we manipulated cue validities within subjects. Cues with validity above 0.5 predicted the outcome; cues with validity below 0.5 and above 0.0 predicted only a slight chance of the outcome or had no relation to the outcome (see Appendix 1).

Table 1. Manipulation of cues in Experiments 1, 2, and 3

Information about the cue–criterion relation		
	Generative	Preventive
High cue validity	Cue 1 (GH)	Cue 2 (PH)
Low cue validity	Cue 3 (GL)	Cue 4 (PL)

Note. Four cues were presented during the experimental task: GH and GL refer to generative cues with high (0.90) and generative cues with low (0.10) validity, respectively; PH and PL refer to preventive high- and preventive low-validity cues, respectively.

In this experiment, two of the four cues (one generative and one preventive) had high validity (i.e., 0.90); the remaining two cues (the remaining generative and preventive cue) had low validity (i.e., 0.10). In sum, participants in both the medical and the financial domain could inspect four different cues to make a decision in each trial: A generative high (GH), a generative low (GL), a preventive high (PH), and a preventive low (PL) validity cue (see Table 1).

After 60 decisions, the two low-validity cues switched to high validity and vice versa; participants were not told of the switch (see Table 2).

Table 2. Experimental procedure in Experiments 1, 2, and 3

Experimental procedure in the medical and financial domains		
	Trial 1–60	Trial 61–120
Experiments 1 & 2	GH, GL, PH, PL	GL, GH, PL, PH
Experiment 3	GH, GL, PH, PL	GL, GL, PH, PH

Note. GH and GL refer to generative cues with high (0.90) and generative cues with low (0.10) validity, respectively; PH and PL refer to preventive high- and preventive low-validity cues, respectively.

The labeling of the cues refers therefore to the induced causal belief (G = generative vs. P = preventive) and the validity of the cue (H = high vs. L = low) before and after the validity switch (cues: GH_GL; GL_GH; PH_PL; PL_PH). All four cues had the same mean discrimination rate in the first and second phase of the decision task (.59) and inter cue correlation was close to zero.[11] Once 60 decisions were completed and again at the end of the task, participants were asked to what extent (on a scale from –10 to +10) each of the four cues (A, B, C, D) would prevent or generate the outcome (either prevent or generate "disease X" or a "decrease in share price" for the medical and financial domain, respectively). A positive (negative) rating implied that the cue generated (prevented) the outcome. A zero rating implied that the cue did not have an effect on the outcome. Participants could base their causal judgments on their accumulated experience during the decision task (i.e., cue validities) or on the instructions they received about the causality of each cue (i.e., causal beliefs). In this and the following experiments, the computerized task was conducted in individual sessions and lasted approximately 1 hr.

Results and Discussion

All analyses contain two main sections. We first report on decision making and then present the results of the causal judgments. We applied a 2 (domain: ***medical*** vs. ***financial***) × 2 (phase: ***before*** vs. ***after*** the validity switch) × 4 (within subject cues) mixed analysis of variance (ANOVA) design to all dependent variables. Post hoc comparisons were all conducted with Fisher's least significant difference test, alpha level .05.

Decision making. The dependent variable decision making measured the proportion of trials that participants decided based on a specific cue given that they searched for the cue and that it discriminated between the two alternatives. As Figure 2 shows, participants were indeed able to adapt their decisions to cue validities. Within the first 60 trials and in both domains, participants favored the high-validity cues over the low-validity cues independently

[11] The discrimination rate of a cue is the proportion of pair comparisons where the cue has different values for

of whether they were generative or preventive. After the validity switch, participants reversed their cue preference to the “new” high validity generative and preventive cues.

In line with these results, a 2 (domain) × 2 (phase) × 4 (cue) ANOVA yielded a significant main effect of cue, $\boldsymbol{F}(3, 90) = 85.63$, $\boldsymbol{MSE} = 214.2$, $\boldsymbol{p} < .001$, partial $\eta^2 = .737$, and an interaction between phase and cue, $\boldsymbol{F}(3, 90) = 4.59$, $\boldsymbol{MSE} = 214.2$, $\boldsymbol{p} = .005$, partial $\eta^2 = .144$. The manipulation of domain did not result in any significant main effects or interactions.

Post hoc comparisons supported the results of the significant interaction (Figure 2). Participants based significantly more decisions on the high-validity than the low-validity cues in each decision phase, independently of domain or the causal version of the cues. Taken together, these results suggest that decisions were only influenced by the empirical evidence experienced during the task and not by the causal beliefs induced via instructions.

Causal judgments. The dependent variable causal judgments revealed a different pattern from that found in decision making (see Figure 2). Participants in the medical domain perceived that generative cues were more likely to indicate the outcome than preventive cues, independently of cue validity (i.e., both before and after the validity switch). In the financial domain, however, induced causal beliefs only showed a little influence in causal judgments after the first decision phase. After the second phase, causal judgments mainly adapted to the cue validities.

In line with these findings, the 2 (domain) × 2 (phase) × 4 (cue) ANOVA showed an interaction between domain, phase, and cue, $\boldsymbol{F}(3, 90) = 2.85$, $\boldsymbol{MSE} = 34.75$, $\boldsymbol{p} = .042$,partial $\eta^2 = .09$, supporting the differences in causal judgments about each cue between the financial and medical domains before and after each decision phase.

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the two alternatives (i.e., when the cue is present in one patient/company and absent in the other; Gigerenzer & Goldstein, 1995).

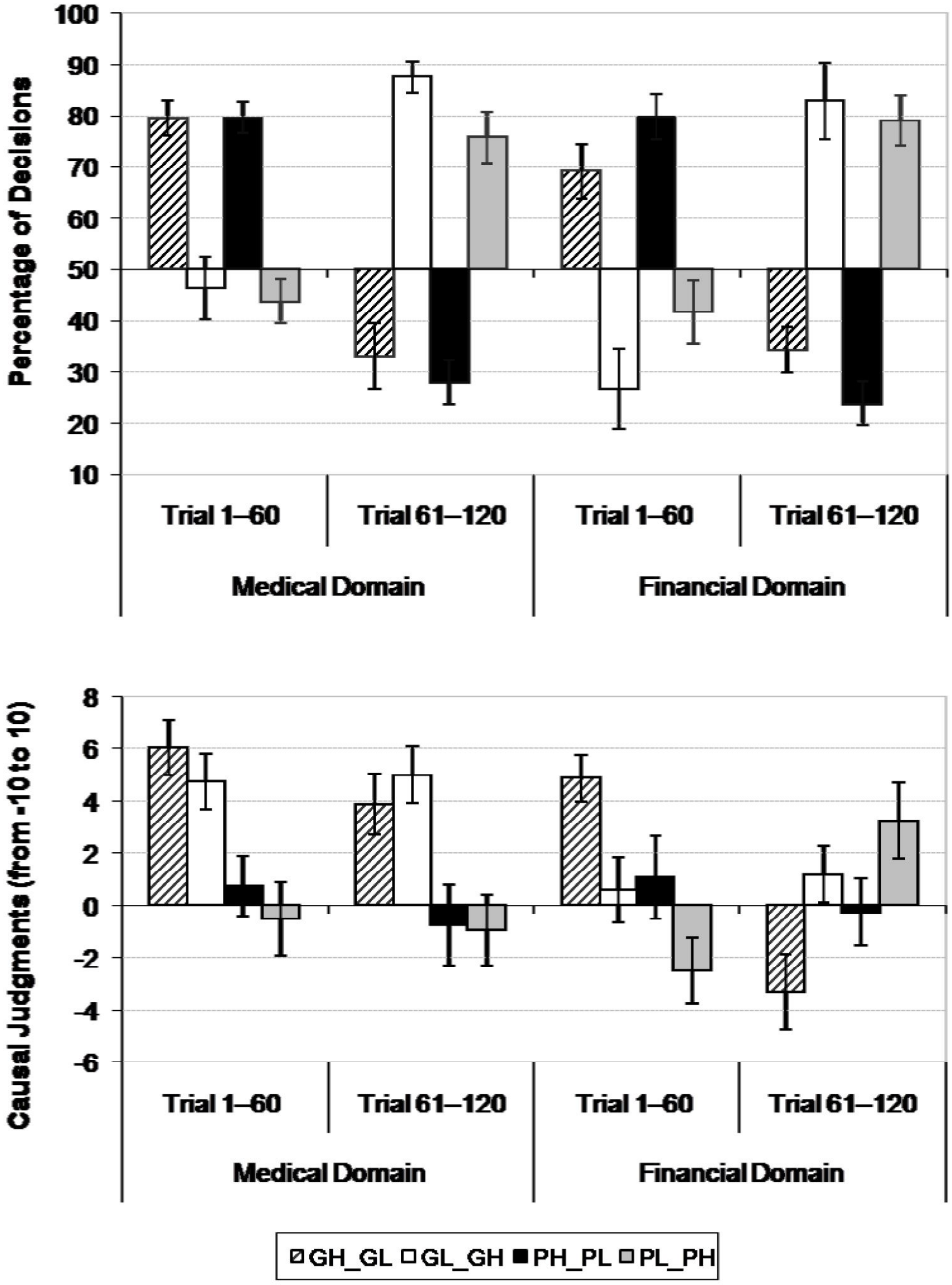

Figure 2. Percentage of trials in which participants' decisions were based on each cue and causal judgments about each cue (GH_GL, GL_GH, PH_PL, PL_PH) in Experiment 1, before (Trial 1–60) and after (Trial 61–120) the validity switch in the decision phase. GH: high-validity generative cue; GL: low-validity generative cue; PH: high-validity predictive cue; PL: low-validity predictive cue. Underscore indicates validity switch. Error bars represent one standard error.

Post hoc comparisons supported the results of the main interactions shown in Figure 2. In the medical domain, results only showed significant differences between generative and preventive cues. In contrast to when they made decisions, participants in this domain disregarded the experienced cue validities during both decision phases when making subsequent causal judgments. In the financial domain, however, participants based their causal judgments on both induced causal beliefs and cue validities after the first phase, but not after the second phase.

In fact, before the validity switch, participants perceived that generative high-validity cues were more likely to indicate the outcome than all other cues; they also perceived that generative low validity and preventive high-validity cues were more likely to indicate the outcome than the preventive low-validity cues (GH_GL>GL_GH = PH_PL> PL_PH). Thus, after the validity switch, participants in the financial domain only relied on the empirical evidence: They considered both "new" high-validity cues to be more likely to indicate the outcome than the "new" low-validity cues (PL_PH>PH_PL and GL_GH>GH_GL).

These results suggest that causal beliefs induced via instructions substantially influenced causal judgments in the medical domain but had only a transitory effect in the financial domain. In contrast, causal beliefs did not influence decision making: Participants' decisions were guided by cue validities in both the medical and the financial domain. Taken together, these findings point to a double dissociation: first, by the differential influence of causal beliefs in the medical and financial domains; second, between decisions and causal judgments in both domains. To further elaborate the influence of causal beliefs, we aimed to extend the findings of Experiment 1 by adding domain-specific information to both (1) the decision outcome in the medical domain (by asking participants to select which of two patients would be more likely to get a ***specific*** disease), and (2) the cues that predict the outcome in both domains.

Experiment 2

Findings of Experiment 1 allow us to draw the conclusion that domain-specific information gained via instructions influenced participants' perception of unspecified cues in causal judgments, but not in decisions. In Experiment 2, we aimed to illustrate the influence of causal beliefs in both the medical and the financial domain by manipulating the generative or preventive version of the cues via domain-specific information and specifying the outcome in the medical domain. Consequently, in Experiment 2 we sought (1) to confirm previous results by mapping whether learned domain-specific beliefs about cues enable people to integrate new evidence in the medical and the financial domain, and (2) to investigate whether these beliefs would also influence decision making in both domains. In this way, we expected to gain further insight about the interplay between causal beliefs and empirical evidence in decision making and causal judgments, and how domain-specific information influences these processes. We expected that, as in Experiment 1, causal beliefs would have a stronger influence in the medical than in the financial domain; we hypothesized that cue validities, in contrast, would have a stronger effect in the financial than in the medical domain.

Method

Participants. Forty-four students (36 women and 8 men, average age of 20 years, range 18–25 years) from the University of Granada, Spain, participated in the experiment. Participants were randomly assigned to one of two equally sized groups (***n*** = 22) and received course credit for their participation.

Procedure and design. Experiment 2 exactly followed Experiment 1, except that:

1. The outcome value was more specified for the medical domain ("occurrence of heart disease" and "decrease of a company's share price," for the medical and financial domain, respectively).
2. We manipulated the generative or preventive version of the cues via domain-specific information.

For instance, in the medical domain, the cues revealed information about whether the two patients exercised, whether they maintained a healthy or unhealthy daily diet, whether they drank alcohol, and their daily amount of stress. In the financial domain, the cues revealed information about the financial health of the two companies: whether the latest report in the ***Financial Times*** was positive or negative, whether the companies were dismissing staff or had new vacancies, whether the strength of the euro was increasing or decreasing, or whether the companies' latest trimestral report was positive or negative (Appendix 2; see also Figure 1, bottom).Again, generative and preventive cues had different outcome values: For instance, in the medical domain, the cue "patients and exercise" could have either a ***generative*** ("never exercises") or a ***preventive*** ("regularly exercises") version (Appendix 2).

Results and Discussion

Decision making. In contrast to the results in Experiment 1, the results in Experiment 2 show a clear effect of causal beliefs in the medical domain, but not in the financial domain (Figure 3). In fact, participants in the medical domain favored the two generative cues over the two preventive cues in the first decision phase. However, they were also sensitive to the cue validity information and decided more often based on the high-validity cues than based on the low-validity cues. After the validity switch, participants in this group still favored both generative cues, followed by the now high validity but preventive cue (PL_PH), which was favored over the low validity preventive one (PH_PL) to make a decision. In contrast, participants in the financial domain were sensitive to the validity information, independently of whether the cues were generative or preventive (causal information).

Consistent with the findings of Experiment 1, the 2 (domain) × 2 (phase) × 4 (cue) ANOVA showed a significant main effect of cue, $\boldsymbol{F}(3, 138) = 4.97$, $\boldsymbol{MSE} = 822.3$, $\boldsymbol{p} = .003$, partial $\eta^2 = .10$, demonstrating that decisions were influenced by the cue validity switch after the first 60 trials in both domains. In contrast to the findings of Experiment 1, participants' decisions differed by cue and domain throughout the task (i.e., causal beliefs had a different influence on decision making in each domain).

Post hoc comparisons revealed that participants in the medical domain decided more often based on the two generative cues than based on the preventive cues, especially during the first phase of the task (GH_GL and GL_GH> PH_PL and PL_PH). Interestingly, participants were also sensitive to cue validities, although this effect was only significant for preventive cues (PH > PL) in each phase. In contrast, participants in the financial domain decided based on the high-validity cues in the first phase of the task (PH_PL, GH_GL); after the validity switch, however, they selected the "new" high-validity cues (GL_GH, PL_PH) to make a decision. In sum, the findings demonstrate that manipulating the generative or preventive version of cues via domain-specific information led to an influence not only of cue validities, but also of causal beliefs (i.e., the causal version of the cues) when participants made decisions in the medical domain. In the financial domain, decisions were only based on cue validities.

Causal judgments. In line with results in the previous experiment, the results in Experiment 2 show that participants' causal judgments differed by domain (Figure 3). In the medical domain, participants perceived generative cues as significantly more reliable indicators of the outcome than preventive cues—both before and after the validity switch, and independently of cue validity. In contrast, participants in the financial domain perceived only high-validity cues as reliable indicators of the outcome—both before and after the validity switch, and independently of whether they were generative or preventive (Figure 3).

Consistently, the 2 (domain) × 2 (phase) × 4 (cue) mixed ANOVA revealed an interaction between domain, phase, and cue, $F(3, 126) = 3.85$, $MSE = 15.07$, $p = .011$, partial $\eta^2 = .08$, illustrating that the causal version of the cues and the validity switch affected causal judgments differently in each domain. Post hoc comparisons supported the results shown in Figure 3.

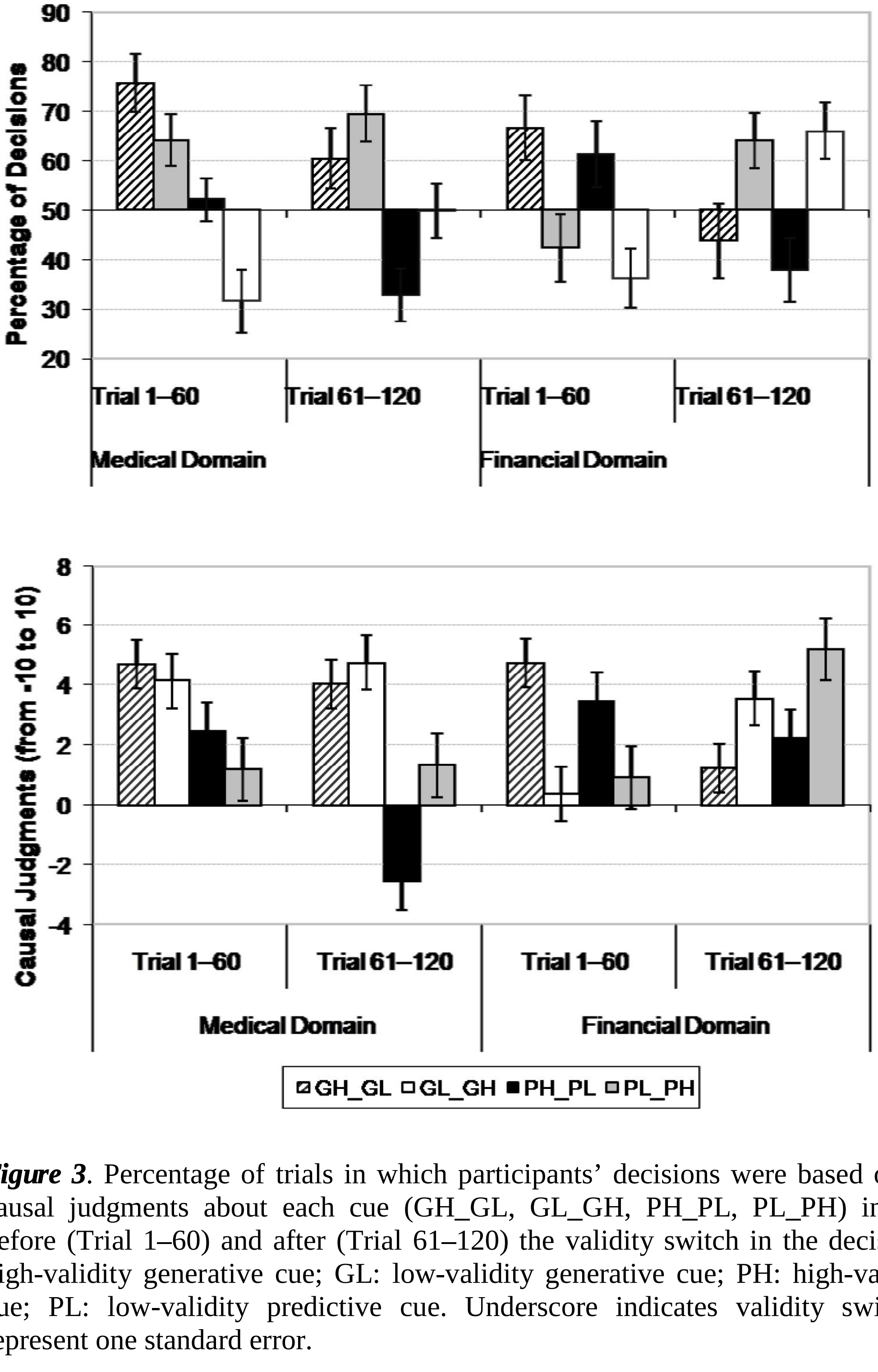

Figure 3. Percentage of trials in which participants' decisions were based on each cue and causal judgments about each cue (GH_GL, GL_GH, PH_PL, PL_PH) in Experiment 2, before (Trial 1–60) and after (Trial 61–120) the validity switch in the decision phase. GH: high-validity generative cue; GL: low-validity generative cue; PH: high-validity predictive cue; PL: low-validity predictive cue. Underscore indicates validity switch. Error bars represent one standard error.

In the medical domain, causal judgments were significantly higher for generative cues than for preventive cues, especially in the second phase of the decision task, and independently of cue validity. Participants were also sensitive to the cue validity and perceived the PH_PL cue as indicating a preventive effect on the outcome after the validity switch. In the financial domain, however, participants always perceived high-validity cues as more reliable indicators of the outcome than the preventive cues, independently of whether they were generative or preventive.

In sum, results in Experiment 2 demonstrate that domain-specific information about the cues differently affected decision making and causal judgments. Indeed causal beliefs influenced causal judgments and decisions to a greater extent in the medical than in the financial domain—participants almost neglected cue validities, especially in causal judgments. In contrast, participants adapted both their decisions and their causal judgments to cue validity in the financial domain, regardless of whether the cues were generative or preventive. As we mentioned above, previous research showed a clear dissociation between decision making and causal judgments. In this experiment, we did not replicate this dissociation within domains, but between them. With a third experiment, we wanted to go one step further in challenging the strength of domain-specific causal beliefs by providing cue validities in the second decision phase that contradicted the initial causal beliefs. With this manipulation, we aimed to gain further insight into the interplay of domain-specific information and the dissociation between decision making and causal judgments in this experiment.

Experiment 3

Experiment 2 revealed two important findings: First, it demonstrated a clear dissociation of decision making and causal judgments between domains: In the medical domain, causal beliefs affected causal judgments ***and*** decision making processes. In the financial domain, however, decisions and causal judgments relied on the cue validities experienced throughout the task. Second, the dissociation between causal judgments and decisions (Experiment 1) disappeared within a given domain when the generative and preventive versions of cues were based on domain-specific information. In Experiment 3, we aimed to investigate whether the influence of causal beliefs in the medical domain persists even with contradictory empirical evidence.

In previous experiments, the reliance on causal beliefs might have been due to the fact that at least one generative cue had high validity during the second decision phase. By setting all generative cues to low validity after the validity switch, none of these cues could lead to a correct outcome in the decision task ("contradictory validity switch"). In sum, this manipulation would lead to a discrepancy between the causal information about the cues (generative vs. preventive) and the experienced empirical evidence (high vs. low validity) and would resemble an unambiguous proof for the influence of causal beliefs given the contradictory empirical evidence. Given previous findings, we hypothesized that causal beliefs would persist even after the contradictory validity switch in the medical domain. Participants therefore would continue to rely on these beliefs despite the contradictory empirical evidence. In the financial domain, we expected participants to adapt their causal judgments and decisions to cue validities, which would be a result consistent with previous experiments.

Method

Participants. Forty-eight students (40 women and 8 men, average age of 22 years, range 19–28 years) from the University of Granada participated in the experiment. Participants were randomly assigned to one of two equally sized groups (***n*** = 24) and received course credit for their participation.

Procedure and design. Experiment 3 exactly followed Experiment 2, except for a different manipulation of the validity switch (see Table 2). After the first 60 trials, (1) both generative cues switched to low validity (i.e., the generative high-validity cue switched to low validity [GH_GL]; the generative low-validity cue maintained low validity [GL_GL]), and (2) both preventive cues switched to high validity (i.e., the preventive low-validity cue switched to high validity [PL_PH] and the preventive high-validity cue maintained high validity [PH_PH]). More precisely, after the validity switch, relying only on preventive cues would lead to the correct outcome feedback throughout the decision making trials. In other words, participants had to adopt a counterintuitive decision strategy to receive positive outcome feedback and to increase their account balance.

Results and Discussion

Decision making. Figure 4 shows that before the validity switch, participants in the medical domain favored the generative cues over the preventive cues for their decisions. This was the case regardless of cue validity, which is consistent with results in Experiment 2. After the validity switch, however, participants did not rely on any of the cues when they made decisions (they favored each cue in approximately 50% of their decisions). In the financial domain, participants detected which cues had high validity and favored these cues in decision making throughout the task. This was the case regardless of whether cues were generative or preventive, which is also consistent with results in Experiments 1 and 2.

In line with these findings, the 2 (domain) × 2 (phase) × 4 (cue) ANOVA showed a significant interaction between domain, phase, and cue, $\boldsymbol{F}(3, 138) = 2.76$, $\boldsymbol{MSE} = 736.32$, $\boldsymbol{p} = .045$, partial $\eta^2 = .06$, and demonstrated that decisions about each cue were affected by the validity switch and differed between domains.

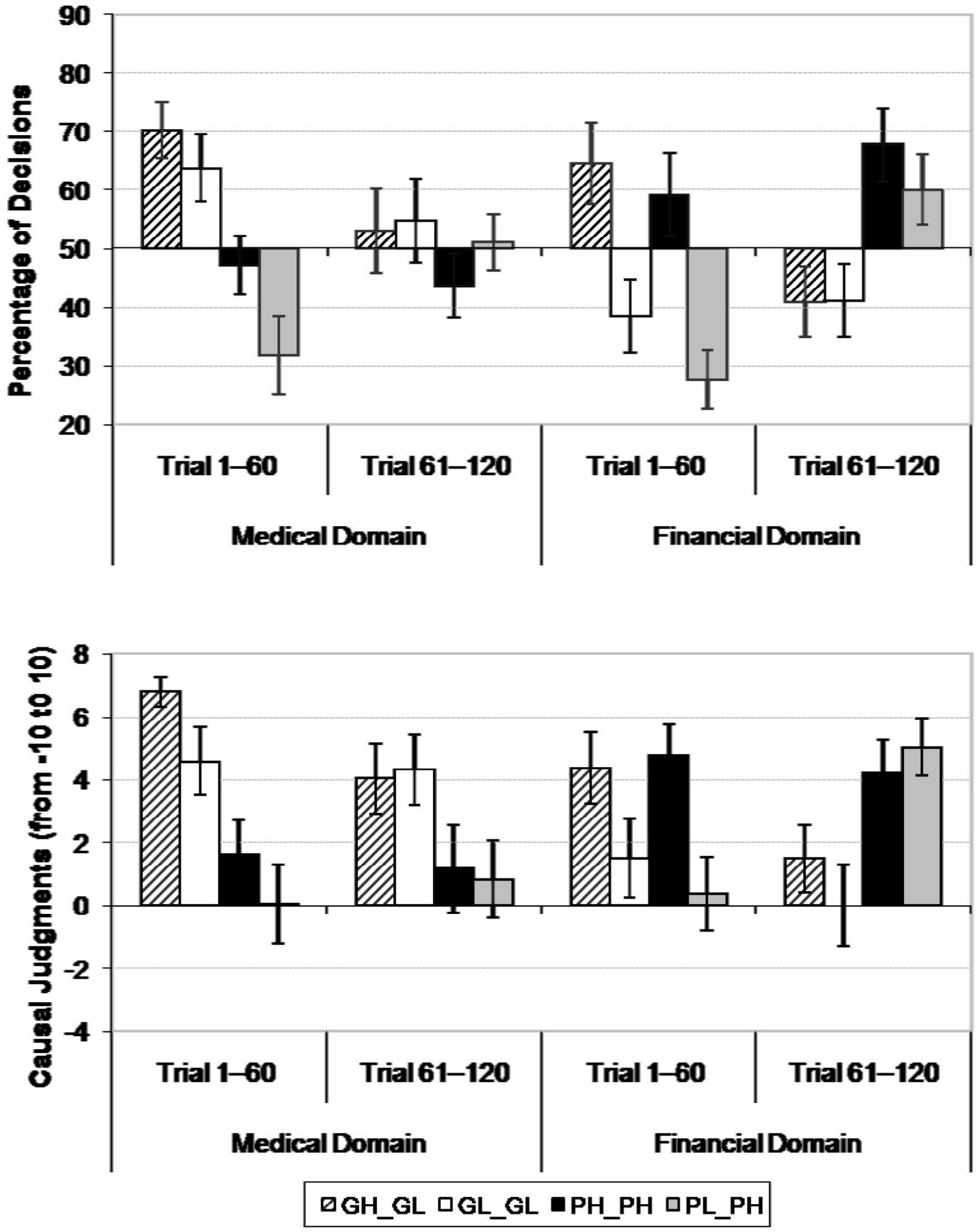

Figure 4. Percentage of trials in which participants' decisions were based on each cue and causal judgments about each cue (GH_GL, GL_GL, PH_PH, PL_PH) in Experiment 3, before (trial 1–60) and after (trial 61–120)the validity switch in the decision phase. GH: high-validity generative cue; GL: low-validity generative cue; PH: high-validity predictive cue; PL: low-validity predictive cue. Underscore indicates validity switch. Error bars represent one standard error.

Post hoc comparisons supported the results shown in Figure 4. In the medical domain, results resembled those in Experiment 1 in the first decision phase: Participants decided based on both generative cues more often than preventive cues. At the same time, they decided more often based on the preventive high-validity cues than the preventive low-validity cues. Interestingly, no differences in decision making occurred after the validity switch, and participants selected cues randomly (around 50%) to make a decision. In the financial domain, participants adapted their decisions to cue validities in both decision phases, regardless of whether they were generative or preventive.

Causal judgments. Results confirmed those of Experiment 2: In the medical domain and before the validity switch, participants perceived both generative cues as more reliable indicators of the outcome. After the validity switch, they still perceived these cues as more reliable indicators of the outcome (i.e., not taking into account the contradictory empirical evidence experienced in the decision task). In contrast, participants in the financial domain judged high-validity cues as more reliable indicators of the outcome and adapted their causal judgments to the manipulation of the cue validities (as they did in decision making).

In line with these results, the 2 (domain) × 2 (phase) × 4 (cue) ANOVA yielded a significant effect for cue, $\boldsymbol{F}(3, 138) = 3.01$, $\boldsymbol{MSE} = 24.31$, $\boldsymbol{p} = .032$,partial $\eta^2 = .06$, and a significant interaction for domain and cue, $\boldsymbol{F}(3, 138) = 7.52$, $\boldsymbol{MSE} = 24.31$, $\boldsymbol{p} < .001$, partial $\eta^2 = .14$, indicating that causal judgments based on certain cues differed between groups. Furthermore, there was an interaction between phase and cue, $\boldsymbol{F}(3, 138) = 5.22$, $\boldsymbol{MSE} = 24.31$, $\boldsymbol{p} = .002$,partial $\eta^2 = .10$, referring to the changes due to the validity switch.

Post hoc comparisons supported the results shown in Figure 4. In the medical domain, participants favored generative cues in their causal judgments over preventive cues. This was the case both before and after the validity switch, thereby confirming the results of the previous experiments. In the financial domain, judgments were based significantly more often on high-validity cues than on low-validity cues throughout the task (independently of their causal version).

In sum, Experiment 3 extended and replicated findings of the previous experiments with a different manipulation of the validity switch ("contradictory validity switch"): All cues that participants believed to generate the outcome switched to low validity in the second decision phase; all preventive cues switched to high validity, thereby encouraging participants to apply a counterintuitive decision strategy. In the medical domain, decisions resembled those of Experiment 2 during the first decision phase: They showed an additive influence of both causal beliefs and cue validities. After the validity switch, however, participants were unable to decide based on any specific cue and made decisions at random (around 50% based on each cue). The same participants still believed that generative and not preventive cues were more reliable for making causal judgments. Results showed some dissociation between decisions and causal judgments in the medical domain. In the financial domain, participants adapted their decisions and subsequent causal judgments to the empirical evidence (consistent with results of Experiment 1 and 2). Consequently, findings confirmed that the influence of causal beliefs is stronger in the medical than the financial domain and showed a clear dissociation between domains on the influence of causal beliefs in decision making and subsequent causal judgments.

General Discussion

Published research illustrates that causal beliefs and empirical evidence influence decision making and causal judgments in a two-alternative forced-choice task. The present work documents that domain-specific information about the decision cues and the outcome crucially affects this influence. In particular, three experiments showed that causal beliefs influence decisions and causal judgments to a greater extent in the medical than in the financial domain. Our experiments showed this result in two different cultures (Germany and

Spain). The result also held independently of whether participants received monetary compensation for their performance.

In the ***medical domain***, causal judgments were always higher about generative cues than about preventive cues, independently of the experienced cue validities during the decision task. This effect appeared when cues were generative and preventive by domain-specific information (Experiment 2 and 3) but also when instructions provided causal information about abstract cues (letters of the alphabet; Experiment 1). The influence of causal beliefs led to a neglect of the empirical evidence, even when all available evidence contradicted previous causal beliefs (i.e., after the validity switch in Experiment 3). Decisions showed an effect of causal beliefs in Experiment 2 and the first decision phase of Experiment 3. In line with previous research (Müller et al., in press), there was also some dissociation between decisions and causal judgments in the medical domain: (1) After the contradictory validity switch in Experiment 3 (i.e., generative cues had low validity and preventive cues had high validity, respectively), participants did not prefer any one cue and made decisions at random but favored generative over preventive cues in causal judgments. (2) When cues revealed only abstract content (Experiment 1), participants adapted their decisions to the cue validities, but they relied on causal beliefs in causal judgments. Here, the monetary compensation, which depended on the points participants had accumulated in the decision task, might have affected their decision strategy and performance.

In the ***financial domain***, decisions and causal judgments were mainly guided by and adapted to the empirical evidence provided via cue validities. Only when instructions provided abstract causal information (Experiment 1) did causal beliefs about the cues have a transitory effect on causal judgments—showing an additive effect of causal beliefs and cue validities after the first, but not the second decision phase.

The differential influence of domain-specific causal information on decisions and causal judgments might be related to the perceived temporal variability of cue validities within a domain, which in turn may affect the strength of a causal belief. We suggested that the dissociation between domains might be due to perceived life-threatening and vital consequences of decisions in the medical domain. People in the medical domain disregarded the empirical evidence in favor of their causal beliefs, in contrast to participants in the financial domain. Findings revealed significant differences between the two domains also in decision making in Experiments 2 and3, when cues revealed domain-specific information. We hypothesize therefore that domain-specific information about causes reduces uncertainty about the perceived temporal variability of cue validities and future consequences inherent in a particular domain. As a result, the dissociation between decisions and causal judgments disappears within a specific domain. Finally, the present results highlight the importance of extending this research to different domains, such as to causal beliefs about people in the social domain (e.g., stereotypes, prejudice, etc.).

These findings have at least three interesting theoretical implications. Recent research has shown that people take causal knowledge into account when making decisions and probabilistic inferences (Lagnado, Waldmann, Hagmayer, & Sloman, 2007; see also Garcia-Retamero, Hoffrage, Dieckmann, & Ramos, 2007). The current findings provide further evidence about the role of previous causal beliefs in decision making and subsequent causal judgments (see also Hagmayer & Sloman, 2009; Müller et al., in press). Such causal knowledge might allow decision makers to reduce the countless number of cues that appear in a particular environment to a subset of cues with high predictive value. In this vein, causal beliefs might act as hypotheses that are tested and updated with empirical data—the confirmation or disconfirmation of these beliefs depends on the strength of previous causal beliefs and the experience with the selected cues in the environment (Koslowski & Masnick, 2002; Meder et al., 2009; Müller et al., in press). Recent theoretical models suggest that causal beliefs act as an anchor that determines the influence of new covariational information (Catena, Maldonado, Perales, & Cándido, 2008; Fugelsang & Thompson, 2003; Lien & Cheng, 2000). The strength of a prior belief and its effect on causal judgments and decisions could be based on the "reliability" of the new evidence, which refers to the degree to which one considers new empirical information (Perales, Catena, Maldonado, & Cándido, 2007; or "plausibility," see Fugelsang & Thompson, 2003). Weak causal beliefs may increase the influence and reliability of the empirical information, resulting in a decreasing impact of previous causal beliefs (similar to in the financial domain). In contrast, strong causal beliefs may decrease the perceived reliability of the empirical information, resulting in a decreasing impact of the empirical information (similar to in the medical domain). In any case, a theoretical model explaining causal learning and judgments must take into account the differential influence of cognitive-based processes—such as prior knowledge and causal beliefs—and empirical evidence—such as cue validities and covariation information.[12]

Second, the present findings highlight the importance of domain-specific information in experiments on decision making and causal judgments. To our knowledge, most research covers only single-domain settings but generalizes results to cognitive processes in other domains. With the comparison of domains in our task, we underline the limitation of such a procedure. We suggest limiting the validity of such results to the domain-specific environment of each experiment until evidence of other domains is available. Causal beliefs may also influence other important domains, such as the social domain, where prejudice and prototypes have been shown to strongly influence decisions and causal judgments (Garcia-

[12] These results could also be considered from a Bayesian point of view: In their support model, Griffiths and Tenenbaum (2005) suggested that a causal judgment reflects one's degree of certainty about the relation between cause and effect. However, operating with four causal candidates (i.e., cues) in our experiments would result in 16 possible models (without taking background causes or a priori likelihoods of these models into account). Developing a Bayesian model that handles this level of complexity could be addressed by future research.

Retamero & López-Zafra, 2006, 2009). The continuum from low to high variability of cue validities might thereby affect the strength of a causal belief. In the medical domain (low variability of cue validities, strong causal belief), decision makers failed to integrate the new evidence (cue validities) adequately; in the financial domain (high variability of cue validities, weak causal belief), participants perfectly adapted their decisions and causal judgments to the empirical evidence.

Third, and in line with previous research (Müller et al., in press), results showed some dissociation between decision making and causal judgments. When participants received abstract information about cues, decisions adapted to the cue validities, whereas causal judgments differed according to the influence of causal beliefs between domains. In both domains, this dissociation disappeared with domain-specific information about cues that predicted the outcome. In the medical domain, more detailed information led to a reliance on causal beliefs primarily, whereas it led to a reliance on the empirical evidence in the financial domain. We suggest, therefore, that perceived certainty about cues decreases the dissociation between decisions and causal judgments. The current experiments not only show that decision making differs according to domain-specific information, but also highlight the need for theoretical models to differentiate the mechanisms and factors underlying decisions and causal judgments. It would be difficult to explain both processes based on a single theoretical framework.

The present findings relate to literature from the medical and the financial domain and may have empirical applications. Strong causal beliefs in the medical domain might be useful to develop coping styles in dealing with diseases. Research has shown that patients are more likely to recover from a disease (Egbert, Battit, Welch, & Bartlitt, 1964; Thomas, 1994) or to attend a rehabilitation program (French, Cooper, & Weinman, 2006) if they perceive personal control of their health status. To establish perceived personal control, people need to perceive certainty about the classification of the disease (i.e., causes) or the expectation of a treatment (i.e., outcome). The strength of causal beliefs about disease and treatment may also explain the success of alternative medicine or the placebo effect (Astin, 1998; Thomas, 1994). On the other hand, literature in economics suggests that decision makers update their current beliefs with the market opinion. Customers' perceived temporal variability of cue validities might form their current beliefs and influence the evaluation of the market; but to construct judgments, the customer again calls upon the market opinion (Munier, 1991). A similar high influence of business news on the variability of the stock market was found (Carroll & McCombs, 2003).

Further research studying the impact of domain specificity on causal beliefs in decisions and judgments could address several points. First, as participants in our study were university students, research is needed to replicate these findings in natural settings, for instance, by comparing causal beliefs in experts and novices in their specific domains (e.g., in doctors vs. patients or brokers vs. shareholders). Second, this line of research should be extended to other relevant domains of life (e.g., moral beliefs, social relationships, or the influence of prejudice). Stereotypes, for instance, resemble commonly shared causal beliefs about certain social groups and their attributes, roles, or behavior. Once a stereotypic belief exists about a certain group, it is highly persistent even when contradictory information is available (Gill, 2004). Finally, individual differences in participants' abilities (e.g., working-memory capacity) might play a crucial role in the reliance on previous beliefs or the competence to detect the empirical evidence by influencing the search strategy of participants in the decision task (Cokely & Kelley, 2009). We aim to address the majority of these issues in further research.

Conclusion

Studies of decision making and causal learning often aim to generalize results to cognitive processes across different domains, although those results were obtained in a single one. Domains may differ, however, in the perceived temporal variability of cue validities and in the extent to which consequences can be life-threatening, among other factors, as for the medical and financial domains. These differences may affect the strength of causal beliefs, which in turn may influence decisions and judgments across certain domains. With the current experiments, we demonstrated that (1) the influence of domain-specific causal information in decisions and causal judgments differs between domains, and (2) causal beliefs have a stronger influence in the medical than the financial domain; accordingly, we showed that (3) the specificity of causal information may influence the perceived certainty about the temporal variability of cue validities or about life-threatening consequences of decision outcomes, and that (4) causal beliefs are more stable and difficult to change than other factors involved in decision making, which could explain some dissociation between decisions and causal judgments, especially in the medical domain. Medical and financial literature support these findings, underlining both the utility of causal beliefs in encouraging certainty and perceived control in medical treatments and the variability of the stock market as a function of most recent news, respectively. Finally, our results highlight the utility of considering both causal beliefs and empirical evidence when drawing theoretical or applied inferences about decision making and causal learning processes.

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Appendix 1

It is important to differentiate between our manipulation of the cue validity and the concept of contingency. The contingency between a candidate cause (cue, $\boldsymbol{c}$) and its effect (outcome, $\boldsymbol{o}$) is defined by $\Delta \boldsymbol{P_c} = \boldsymbol{P}(\boldsymbol{o}|\boldsymbol{c}) - \boldsymbol{P}(\boldsymbol{o}|\neg \boldsymbol{c})$,where $\boldsymbol{P}(\boldsymbol{o}|\boldsymbol{c})$ is the probability of $\boldsymbol{o}$ given the presence of $\boldsymbol{c}$ (i.e., validity of the cue, which was manipulated in the studies presented here) and $\boldsymbol{P}(\boldsymbol{o}|\neg \boldsymbol{c})$ is that probability given the absence of $\boldsymbol{c}$. In contingency terms, a positive $\Delta \boldsymbol{P_c}$ value refers to $\boldsymbol{c}$ as a ***generative*** or excitatory cause; a negative $\Delta \boldsymbol{P_c}$ value refers to $\boldsymbol{c}$ as a ***preventive*** or inhibitory cause; a $\boldsymbol{c}$ value around zero means that cue and outcome are unrelated (Lien & Cheng, 2000).

To meet the requirements for a decision task following Gigerenzer et al. (1999), we manipulated cue validity. To serve our interest in causal judgments, we also calculated the contingency values for each cue after the experiment. High-validity cues (i.e., 0.90) resulted in a contingency between 0.50 and 0.60; low-validity cues (i.e., 0.10) resulted in a contingency between 0.00 and –0.20 (mean contingency was –0.10, confirming that the cue had no relation to the outcome).

Appendix 2

Cue	Preventive version	Generative version
	Medical domain	
Exercise	Regularly does exercise	Never does exercise
Daily diet	Vegetables and low fat food (e.g., whole grains, little meat)	Food high in calories and fat (e.g., white bread, French fries)
Amount of stress	Living without any stress	Living a stressful life
Alcohol consumption	Alcohol abstinence	Consuming high quantities of alcohol
	Financial domain	
The ***Financial Times*** offers a daily report about the stock market.	The latest report was promising	The latest report was negative
Vacancies or work dismissals can be a sign of a company's well-being.	The company has new vacancies	The company dismisses staff
The strength of the euro is directly related to the financial market and affects the value of shares.	There has been an increase in the strength of the euro	There has been a decrease in the strength of the euro
Companies normally publish a trimestral report about their effectiveness, gains and losses.	The trimestral report was positive	The trimestral report was negative

Note: Material used in Experiments 2 and 3: Generative and preventive versions of four cues that participants could use to determine which of two patients would be more likely to develop heart disease or which of two companies would be more likely to experience a decrease in their share price.

Independent naïve participants (n=51) rated the extent to which generative or preventive cues generated or prevented the outcome on a scale from 10 (positive relationship) to -10 (negative relationship). Generative cues were judged to generate the outcome (M_{Stock}=4.87;M_{Heart}=5.36) and preventive cues were judged to prevent the outcome, M_{Stock}=-3.85, F(4, 46)=0.173, p<.001;M_{Heart}=-4.2, F(1, 46)=0.19, p<.001, respectively. There was no difference in perceived causal strength between domains (stock market vs. heart disease), neither for generative, F(4, 41)=0.89, p=.277, nor for preventive, F(4, 51)=0.95, p=.62, cues, respectively. No difference was observed in the perceived strength of the relatedness with the outcome among generative, F_{Stock}(3, 66)=5.42, p=.286; F_{Heart}(3, 66)=10.446, p=.128, or preventive, F_{Stock}(3, 81)=1.75, p=.872; F_{Heart}(3, 81)=12.036, p=.424, cues, respectively.

CHAPTER 4

Judgment frequency as an adaptive tool in decision making and causal judgments[13]

Abstract

We conducted two experiments to map the influence of causal beliefs and judgment frequency (i.e., the frequency people make a causal judgment) on decisions and causal judgments in different domains (medical vs. financial). Previous research indicates that people are more susceptible to empirical evidence when they have to make several causal judgments that just one global causal judgment (Catena, Maldonado, & Cándido, 1998). Participants made 120 decisions in a two-alternative forced-choice task—framed either as medical or financial diagnostic task—on the basis of four predictive cues. To examine the strength of the causal belief, we manipulated the predictive power (i.e., cue validities) and the causal relation with the outcome (i.e., generating vs. preventing) of the cues. In addition, we manipulated judgment frequency (high vs. low) between participants. Results revealed a double dissociation: (1) between domains in causal judgments and (2) between decisions and causal judgments in both domains. Judgment frequency affected the degree people take empirical evidence into account. We conclude that a theoretical model that tries to account for these findings has to integrate both, the strength of a causal belief and the reliability of the new evidence to explain the current findings in decision making and causal judgments.

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Introduction

Adaptation and learning serve as basic tools to survive in a changing environment, but they require the ability to integrate new information. For instance, the Japanese society relied on supposed safety of its nuclear power system for decades—until the earthquake and tsunami on the 11th of March 2011 added strong and dreadful evidence to falsify these beliefs (Clenfield, 2011). People therefore have to engage in a delicate balance between conviction and flexibility to update their previous causal beliefs with the new evidence gathered from the environment.

To deal with the vast amount of information in the environment, people often apply mental models about cause-effect relationships (Garcia-Retamero, Wallin, & Dieckmann, 2007; Waldmann, Hagmayer, & Blaisdell, 2006). These causal beliefs can boost the decision making process, but can also lead to a neglect of the empirical evidence (Garcia-Retamero, Müller, Catena, & Maldonado, 2009). However, causal beliefs can be updated by empirical evidence. Einhorn and Hogarth (1985) demonstrated that causal beliefs can be modified by a sequential anchoring-and-adjustment process in which people revise their causal beliefs every time they are asked about cause-effect relationships. In other words, when presented with new evidence between two consecutive judgments, they use the first judgment as an anchor and adjust it in face of the new evidence to make the second judgment. Thus, judgments are not simply a reflection of initial causal beliefs, but are a product of these beliefs and empirical evidence.

In a similar vein, Catena, Maldonado, and Cándido (1998) investigated different factors contributing to changes in causal beliefs. They suggested the ***Belief Revision Model*** (BRM; Catena et al., 1998), an anchoring-and-adjustment mechanism—similar to an earlier approach by Hogarth and Einhorn (1992)—to map the interplay between causal beliefs and empirical evidence and their influence on causal judgments. This additive model proposes that the main factors influencing the updating of causal beliefs are the ***strength*** of previous causal beliefs, the ***sign and strength*** of new empirical evidence to update previous causal beliefs, and the ***relative reliability*** that people attribute to such new evidence (see general discussion for a thorough explanation of the model).

In many everyday contexts (e.g., the stock market or in the health domain) people frequently make decisions based upon causal judgments (Hardman, 2009). Because decision outcomes are often delayed or unknown, the accumulated amount of new evidence obtained between several consecutive causal judgments is often rather small. Smaller samples of evidence typically have lower reliability and replicability (Tversky & Kahnemann, 1974). Findings show, however, that the influence of new evidence on causal judgments does not decrease monotonically with sample size—as demonstrated by the frequency-of-judgment effect (Catena, et al., 1998; Einhorn & Hogarth, 1985; Pennington & Hastie, 1992; Perales et al., 2007). In the corresponding experimental design, participants have to make causal judgments frequently during the presentation of empirical evidence, which is either in favor or against a given hypothesis (e.g., that regular exercise decreases the likelihood of a heart disease). In general, results show that the sign of the very last pieces of information strongly influences causal judgments (more precisely, the ***average sign*** of the information presented since the last causal judgment). However, when participants make only a single global causal judgment about a whole series of information, they tend to average all the evidence. Consequently, judgment frequency may enhance people's susceptibility to new evidence.

The adaptive process to integrate new information may not be equally valid for all domains. Recent research has shown that peoples' decisions and causal judgments in the medical domain differ from those in the financial domain, as people hold stronger causal beliefs in the medical than the financial domain (Garcia-Retamero & Galesic, 2011; Müller, Garcia-Retamero, Galesic, & Maldonado, 2011). For instance, some medical practitioners seem to be resistant against changing their initial assumptions about medical treatments (Tatsioni, Bonitsis, & Ioannidis, 2007). In the same vein, Brian Haynes (2009) "raised alarm" about physicians who keep relying on outdated treatments by contradicted evidence. This inflexibility to change previous causal beliefs also occurs among researchers (Fugelsang, Stein, Green, & Dunbar, 2004). In contrast, in the financial domain people appear to show overdependence on the most recent bits of information they received. This tendency may be one of the causes of volatility in investment decisions on the stock market (De Bond & Thaler, 1985; Fung, Lam, & Lam, 2010). These results highlight the importance to control for domain-specific information when mapping the influence of causal beliefs on decisions and causal judgments.

The novel contribution of the present study is to investigate the interplay of causal beliefs and judgments frequency in two different domains using a two-alternative forced-choice task. We address two major questions: First, given the evidence that causal beliefs in some domains are more resistant to change than others (Müller et al., 2011), we investigate to what extent causal beliefs in different domains are susceptible to change in tasks involving high judgment frequency. Second, previous research has demonstrated that the interplay between causal judgments and decisions is relatively poorly understood and that there is a dissociation between the two processes (Müller, Garcia-Retamero, Cokely, & Maldonado, in press; see Garcia-Retamero, Hoffrage, Müller, & Maldonado, 2010 for a review). Accordingly, we investigate how judgment frequency affects this dissociation. In this way, we intended to clarify whether the (in)flexibility of causal beliefs stems from the strength of the previous causal beliefs (the anchor in the anchoring-and-adjustment heuristic) or from the reliability attributed to the new evidence.

Experiment 1

To assess to what extent causal beliefs are sensitive to anchoring-and-adjustment effects in different domains, we manipulated the judgment frequency and the domain-specific information provided in the experimental task. Participants had to make 120 decisions about which of two alternatives had a higher criterion on the basis of four available cues. Random half of participants received tasks embedded in the ***medical domain*** (the cues concerned different aspects of the behavior of a patient) and the other half in the ***financial domain*** (the cues reflected different aspects of the performance of a company, see Appendix 1). Within each domain, random halves of participants differed in the amount of causal judgments required throughout the task (see also Catena et al., 1998). In particular, two groups (one each in medical and in financial domain) made only a single causal judgment about each cue at the end of the decision task (***low judgment frequency*** group). The remaining two groups (again one each in medical and in financial domain) judged the extent to what each cue predicted the outcome at the beginning of the task and after every forty decisions (***high judgment frequency*** group).

In line with previous research on the frequency-of-judgment effect (Catena, et al. 1998), we hypothesized that participants in the high judgment frequency group would update their decisions and causal judgments according to the empirical evidence (i.e., cue validities) to a greater extent than participants in the low judgment frequency group. We further hypothesized that domain-specific information would influence causal judgments and that participants would rely on their causal beliefs to a greater extent in the medical than the financial domain (Müller et al., 2011). Finally, as our latest findings indicated dissociation between decisions and causal judgments (Müller, et al., in press), we hypothesized that decisions would adapt to the empirical evidence to a greater extent than causal judgments, especially in the higher judgment frequency conditions. Consequently, we expected a double dissociation: (1) between decisions (adapting to the empirical evidence) and causal judgments (relying on the previous causal information) and (2) between domains—we anticipated that participants rely on causal information to a greater extent in the medical than the financial domain, especially in causal judgments.

Method

Participants. Sixty-four students (54 women and 10 men, mean age = 20 years, range 18–26 years) from the University of Granada, Spain, participated in the experiment for course credit. Participants were randomly assigned to one of four equally sized groups (***n*** = 16).

Procedure. First, participants were instructed to choose between two alternatives (displayed column-wise) and select the one with the higher outcome value (decision task). Participants in the medical group had to choose between two patients and select "the patient, who would be more likely to get a heart disease." Participants in the financial group had to choose between two companies and select "the company, which would be more likely to experience a decrease in its share price" (see Figure 1). Four selectable cues described the two alternatives (patients or companies). In both groups, participants had to search for at least one cue to make a decision. The order of the four cues—presented as little boxes on the screen—was fixed for each participant, but varied randomly between participants (see also Bröder, 2003; Müller et al, in press, for similar experimental procedures).

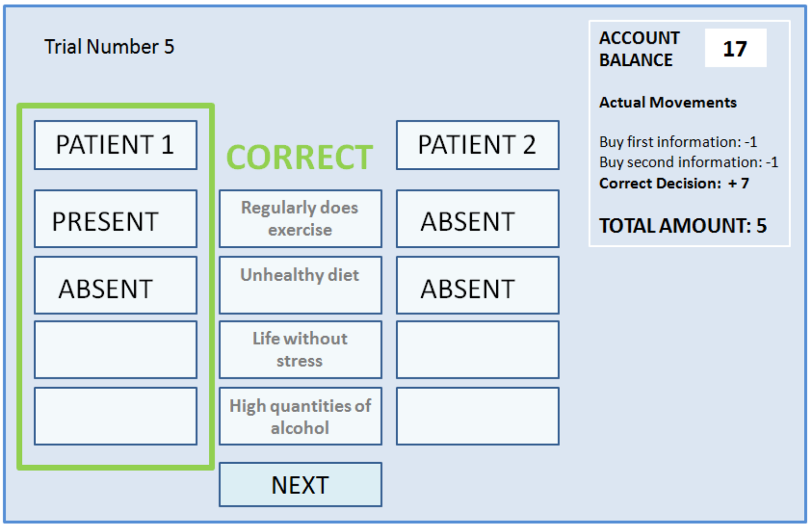

Figure 1. Screenshot of the experimental task in Experiments 1 and 2. In this example, the participant began information search with the cue describing whether the patients were maintaining an "unhealthy diet." This cue uncovered a negative value for Patient 1 and a positive value for Patient 2. The participant next searched whether the patients were "regularly exercising." This cue did not discriminate between the two patients, as neither of them was exercising regularly. Two points have been subtracted from her account for looking up these two cues. The participant decided that Patient 2 would be more likely to develop heart disease—a correct decision that led to a gain of 5 points in this trial.

Whenever a box was selected to retrieve information about the value of a cue, the information on whether the cue was absent or present appeared simultaneously for both alternatives on the screen and remained visible until a decision was made. After completing the cue search, participants made a decision by clicking on a button (i.e., selecting one of the two patients or companies), and then received feedback about the correctness of the decision. Participants made 120 decisions with no time constraints (divided into three blocks of 40 trials). Each participant received the same set of trials within each block and in random order. Their current account balance was always visible on the computer screen and participants were told to strive to maximize the number of points. For each cue looked up, 1 point was deducted from the overall total; participants could gain 7 points for each correct decision.

Additionally, participants were asked to what extent (on a scale from −10 to 10) each of the four cues would prevent or generate the outcome (either prevent or generate a “heart disease” or “decrease in the share price” for the medical and financial domain, respectively). A positive (negative) rating implied that the cue caused (prevented) the outcome. A zero rating implied that the cue did not have an effect on the outcome. In the high judgment frequency groups (one medical and one financial group), participants had to give a “causal judgment” for each cue four times: At the beginning of the decision task, after every 40 decisions, and at the end of the task. Participants in the low judgment frequency groups made only one final causal judgment for each cue at the end of the decision task. In this and the following experiments, the computerized task was conducted in individual sessions and lasted one hour approximately.

Design. To analyze the influence of causal beliefs, we manipulated causal beliefs within-subjects. In particular, we instructed participants that two of the four cues generated the outcome (***generative cues***), whereas the remaining two cues prevented the outcome (***preventive cues***). For instance, in the medical domain, the cue “patients and exercise” could have either a ***generative*** ("never does exercise") or a ***preventive*** version ("regularly does exercise;" see Appendix 1).

To measure the sensitivity to empirical evidence, we manipulated cue validities within-subjects. We refer to the validity of a cue as the probability that it leads to a correct decision, given that it discriminates between the alternatives (Gigerenzer, Todd, & the ABC Research Group, 1999). Cue with validity above 0.5 predicted the outcome; cue with validity below 0.5 and above 0.0 predicted only a slight chance of the outcome or no relation to the outcome (see Appendix 2). Two of the four available cues (one generative and one preventive) had high validity (i.e., 0.90); the remaining two cues (the remaining generative and preventive cue) had low validity (i.e., 0.10). In sum, participants in both the medical and the financial domain could inspect four different cues to make a decision in each trial: A generative high- (GH), a generative low- (GL), a preventive high- (PH), and a preventive low- (PL) validity cue (Table 1).

Table 1. Manipulation of cues in Experiment 1and Experiment 2

Information about the cue-criterion relation		
	Generative	**Preventive**
High cue validity	Cue 1 (GH)	Cue 2 (PH)
Low cue validity	Cue 3 (GL)	Cue 4 (PL)

Note. Four cues were presented during the experimental task: GH and GL refer to generative high (0.90) and generative low validity cues (0.10); PH and PL refer to preventive high and preventive low-validity cues.

All four cues had a similar mean discrimination rate (0.59) and inter-cue correlation was close to zero. The discrimination rate of a cue is the number of pair comparisons with different alternatives (i.e., when the cue is present in one patient/company and absent in the other).

Results and Discussion

All analyses contain two main sections. We first report on participants' decisions, and then present the results of the causal judgments. Post hoc comparisons were all conducted with Fisher LSD test, alpha-level 0.05.

Decision making. The dependent variable ***decision making*** measured the proportion of trials that participants made a decision based on a specific cue given that the cue discriminated between the two options (see Müller et al., in press). Figure 2 shows that participants in all four groups adapted their decisions to cue validities during the experiment. We applied a 2 (domain: ***medical*** vs. ***financial***, between subjects) × 2 (judgment frequency: ***high*** vs. ***low***, between subjects) 4 × (cue: GH, GL, PH, PL; within subjects) ANOVA design to the final block of the dependent variable decision making. The ANOVA showed an interaction of cue and judgment frequency, $F(3, 180) = 4.352$, $MSE = 748.1$, $p = 0.005$, partial $\eta^2 = 0.068$, indicating differences between cues in groups who made causal judgment frequently compared with those who only made a single causal judgment at the end of the task. There was also a significant effect of cue, $F(3, 180) = 81.133$, $MSE = 748.1$, $p = 0.001$, partial $\eta^2 = 0.575$, indicating that participants decided more often based on high-validity cues than low-validity cues.

Post hoc tests revealed that participants in the high judgment frequency groups adapted to the empirical evidence to a greater extent than those in the low judgment frequency groups. Participants in all groups decided based on high-validity cues over the low-validity cues. There was also a slight preference for the generative over the preventive high-validity cue (GH > PH). Furthermore, low judgment frequency groups additionally showed a preference for generative over preventive low valid cues (GL > PL) in decision making. This difference did not occur in the high judgment frequency groups (GL = PL), as these participants adapted to the empirical evidence to a greater extent. Taken together, results of decision making mainly resembled the manipulation of the empirical evidence, but also indicated a small additive effect of causality and validity.

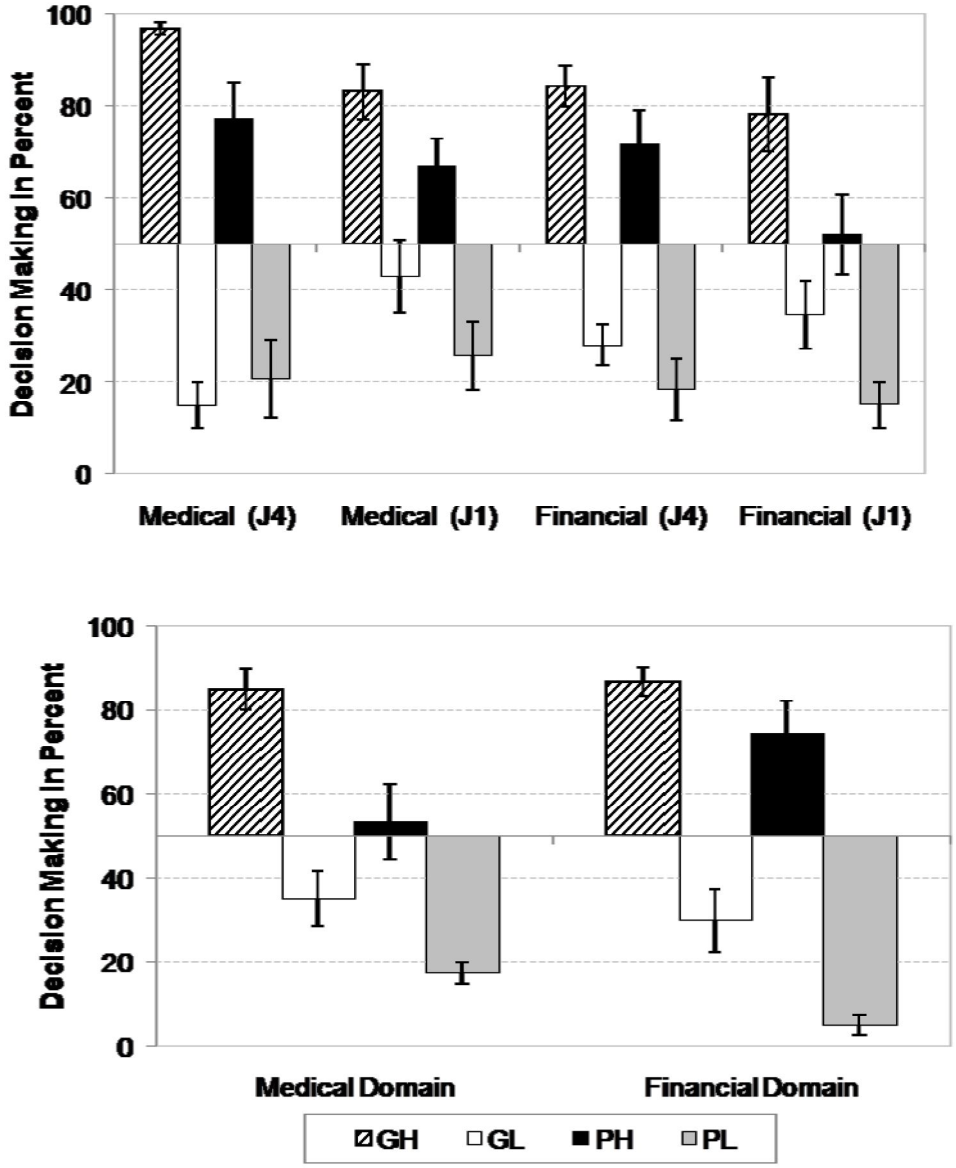

Figure 2. Percentage of trials in which participants' decisions were based on each cue (GH, GL, PH, PL) in Experiment 1 and 2. GH: high-validity generative cue; GL: low-validity generative cue; PH: high-validity predictive cue; PL: low-validity predictive cue. Error bars represent one standard error.

Causal judgments. Figure 3 demonstrates that the judgments frequency influenced causal judgments differently in the medical and the financial domain. In particular, causal beliefs had a greater influence in the medical domain than in the financial domain.

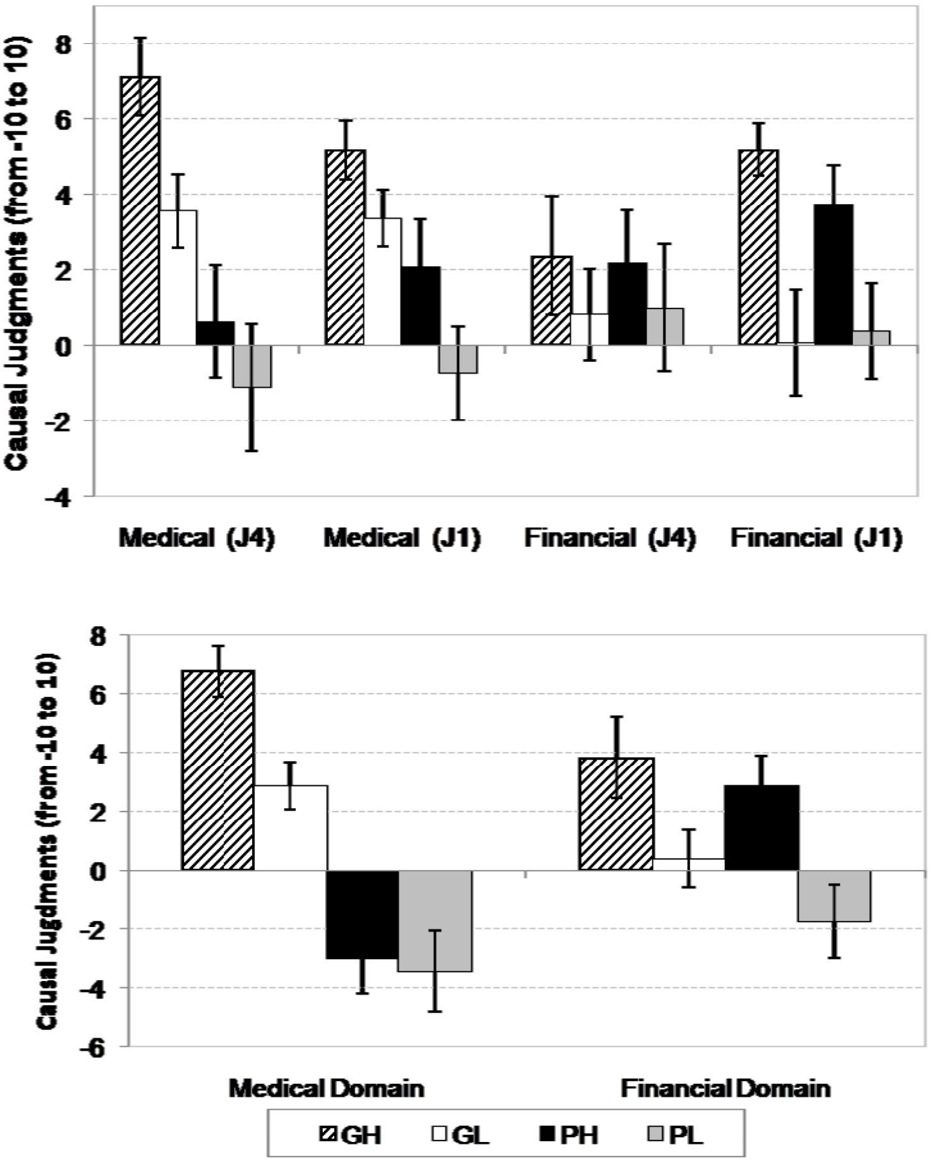

Figure 3. Causal judgments about each cue (GH, GL, PH, PL) in Experiment 1 and 2. GH: high-validity generative cue; GL: low-validity generative cue; PH: high-validity predictive cue; PL: low-validity predictive cue. Error bars represent one standard error.

We applied a 2 (domain: ***medical*** vs. ***financial***, between subjects) × 2 (judgment frequency: ***high*** vs. ***low***, between subjects) 4 × (cue: GH, GL, PH, PL; within subjects) ANOVA design to the dependent variable causal judgment at the end of the task. The ANOVA showed a significant interaction of domain and cue, $F(3, 180) = 3.936$, $MSE = 22.549$, $p = 0.009$, partial $\eta^2 = 0.062$, and an effect of cue, $F(3, 180) = 13.811$, $MSE = 22.549$, $p = 0.001$, partial $\eta^2 = 0.187$, indicating that participants differed in their perception of which cue(s) would indicate the outcome in the two domains.

Post hoc tests supported these conclusions showing that in the medical domain, participants' causal judgments showed an influence of previous causal beliefs. They perceived the generative high-validity cue followed by the generative low-validity cue as most likely to indicate the outcome (GH > GL). Findings in the financial domain were more diverse: Participants in the high judgment frequency group did not perceive any specific cue to indicate the outcome. Those in the in the low judgment frequency group clearly perceived both high-validity cues as most likely to indicate the outcome (GH = PH > GL = PL).

Experiment 1 revealed two main findings: (1) Judgment frequency increases the reliance on empirical evidence in decision making—that is, decisions resembled the empirical evidence to a greater extent in the high than in the low judgment frequency group—and (2) domain-specific information had a differential impact on causal judgments in the two domains: Causal beliefs were stronger in the medical than the financial domain. In line with previous research, results showed a double dissociation: (1) between decisions and causal judgments, and (2) between domains in causal judgments. In Experiment 2, we aimed at extending and replicating the current findings in another cultural context and including monetary compensation of participants' task performance.

Experiment 2

Experiment 1 demonstrated that participants in the medical domain judged generative cues as more likely to indicate the outcome (independent of cue validity), whereas participants in the financial domain judged high-validity cues to be more likely indicating the outcome (independent of their generative or preventive relation with the outcome). To demonstrate the generality of the finding that previous causal beliefs influence decisions and causal judgments as a function of domain, Experiment 2 was conducted with participants from a different cultural context (Germany vs. Spain). Additionally, previous research has shown that motivational factors (such as monetary compensation of participants' performance) lead to different experimental outcomes, as they enhance participants' performance due to the reward expectation in the task (Vulkan, 2000). Therefore, to add further evidence to the reliability of previous findings—i.e., that decisions and causal judgments differ in their reliance on previous causal beliefs and empirical evidence—participants were given a monetary compensation for the accumulated points of their participation.

Method

Participants. Thirty-two students (13 women and 19 men, mean age = 27 years, range 21–31 years) from the Free University of Berlin, Germany, participated in the experiment for monetary compensation. Participants were randomly assigned to one of two equally sized groups ($n = 16$).

Procedure and Design. Experiment 2 exactly followed Experiment 1, except that (1) we only applied high judgment frequency, (2) participants were German, and (3) they received a monetary compensation for the accumulated points of their participation at the end of the experiment.

Results and Discussion

Decision making. As expected from results in Experiment 1, participants made their decisions differently depending on the domain (Figure 2).

We applied a 2 (domain: ***medical*** vs. ***financial***, between subjects) × 4 (cue: GH, GL, PH, PL; within subjects) ANOVA design to the final block of the dependent variable decision making. The ANOVA showed a significant interaction between domain and cue, $F(3, 90) = 2.710$, $MSE = 613.563$, $p = 0.049$, partial $\eta^2 = 0.083$, indicating differences in cue selection to make a decision depending on the domain.

Post hoc tests supported the findings shown in Figure 3. In the medical domain, participants decided based on the generative high-validity cue (over all other cues)—indicating an additive effect of causality and validity. The preference for this cue followed decisions based on the preventive high-validity cue over all low-validity cues. There was also a preference for the generative low-validity over the preventive low-validity cue (GH > PH > GL > PL). In the financial domain, participants decided based on high-validity cues, independent of their generative or preventive version. These participants also preferred the generative low-validity cue over the preventive low-validity cue (GH = PH > GL > PL).

Causal judgments. Similarly to Experiment 1, Figure 3 demonstrates that causal judgments differed between the medical and the financial domain. This difference, however, results in a clearer distinction between domains than in Experiment 1.

We applied a 2 (domain: ***medical*** vs. ***financial***, between subjects) × 4 (cue: GH, GL, PH, PL; within subjects) ANOVA to the dependent variable final causal judgment. Results revealed an interaction between domain and cue, $F(3, 90) = 6.429$, $MSE = 21.202$, $p = 0.001$, partial $\eta^2 = 0.176$.

Post hoc tests showed that participants in the medical domain perceived the generative cues as more likely to indicate the outcome, independent of their validity. There was also a preference for the generative high-validity cue over the generative low-validity cue (GH > GL > PH = PL), indicating and additive effect of causality and validity (similarly to Experiment 1). In the financial domain, participants adapted their causal judgments to the cue validities experienced throughout the decision task: They preferred both high-validity over the low-validity cues to make a causal judgment, independently of their generative or preventive version (GH = PH > GL > PL). These results could not be explained by differences in the search process.[14]

[14] Given the differences in cultural context and monetary compensation, we analyzed whether participants differed in their search process between countries. For the Spanish sample (Experiment 1), we applied a 4 (group) × 3 (block) 4 × (within subjects cues) mixed ANOVA design to the dependent variable cue search. Results revealed an effect of block, $F(2, 120) = 19.109$, $MSE = 29.2$, $p = 0.001$. For the German sample (Experiment 2), we applied a 2 (domain: ***medical*** vs. ***financial***) × 3 (block) × 4 (within subjects cues) mixed ANOVA to the dependent variable cue search. Results also revealed an effect of block, $F(2, 60) = 15.157$, $MSE = 21.1$, $p = 0.001$. In both cases, post hoc tests indicated a higher cue search in the first block of decision making compared with the second and third block. Consequently, neither the monetary compensation of participants nor the cultural context produced any differences in cue search.

Taken together, Experiment 2 supported the findings of Experiment 1. Domain-specific information influenced causal judgments: Causal beliefs had a greater influence in the medical than the financial domain. Decisions, however, resembled the manipulation of cue validities—although there was also an additive effect of causality and validity in the medical domain. Again, results showed a double dissociation: (1) between domains in causal judgments, and (2) between decisions and causal judgments.

General Discussion

The present studies manipulated judgment frequency in a two-alternative forced-choice task including four predictive cues, which differed in their causal relation to the outcome (preventive vs. generative) and validity (high vs. low). To map differences in the strength of causal beliefs, the task was set up in two different domains (medical vs. financial). Overall, the experiments showed three main results.

First, people updated their decisions and causal judgments with the frequency of a causal judgment (e.g., Catena et al., 1998; Perales et al., 2007). In the last block of decision making, participants clearly adapted to the cue validities—to a greater extent in the high than the low judgment frequency condition. In final causal judgments, domain-specific differences (see below) were more pronounced in the high compared with the low judgment frequency group. This is an interesting finding, as the frequency-of-judgment effect has not been tested in such a complex task, which manipulated validity, causality, and domain-specific information.

Second, domain-specific differences appeared in causal judgments and partly in decisions. In the medical domain, participants showed a clear influence of causal beliefs on final causal judgments, as well as in the last block of decision making when they received a monetary compensation for the points they earned. In the financial domain, participants adapted their final causal judgments to the empirical evidence provided throughout the task.

An exception was the high judgment frequency group without monetary compensation, where participants judged all cues to predict the outcome equally low (around +2).

Third, in line with previous work (Müller et al., 2011), we observed a double dissociation: (1) Between domains indicating a strong influence of (previous) causal beliefs in the medical domain but not in the financial domain, and (2) between decisions and causal judgments showing a stronger influence of cue validities on decision making than causal judgments. As the terms decisions and judgments are often used interchangeable (see Hardman, 2009), the present findings highlight the necessity for a theoretical model to differentiate between these two processes.

Several approaches have been made to map decision making. For instance, Gigerenzer and the ABC Research Group proposed the ***fast and frugal heuristics research program*** (Gigerenzer, Todd, & the ABC Research Group, 1999; Todd, Gigerenzer, & the ABC Research Group, in press), and showed that among other heuristics, people often use a noncompensatory decision strategy called ***take-the-best*** (Gigerenzer & Goldstein, 1996, 1999). Take-the-best has been developed for two-alternative forced-choice tasks, similar to the one applied in our experiments. This heuristic is constructed from three building blocks: A ***search rule*** (take-the-best looks up the cue with the highest validity), a ***stopping rule*** (take-the-best stops after the first discriminating cue), and a ***decision rule*** (take-the-best chooses the alternative after the first discriminating cue). Participants in studies showing that people use take-the-best often get information about cue validities or are encouraged to use cues in order of their validity (e.g., Bröder, 2003). Consequently, a comparison with other search strategies revealed that validity did not predict best people's search processes (Newell, Rakow, Weston, & Shanks, 2004). In many daily life-contexts, computing validity would be intractable considering the fact that people face countless potential cues in the environment that can be used to make a decision (Juslin & Persson, 2002; see also Garcia-Retamero et al., 2007).

There are also strategies that use compensatory processing of cues to make decisions, as for instance the weighted additive linear model (WADD; Martignon & Hoffrage, 2002). WADD first computes the sum of all cue values multiplied by the cue weights for each alternative and then chooses the alternative with the largest sum. However, compensatory strategies such as WADD do not model people's search process. None of the decision strategies mentioned above (either compensatory or noncompensatory) takes into account the potential benefit of using causal knowledge to reduce the computational complexity in decision making by selecting the number of cues that are taken into account.

Various theoretical approaches have addressed the relation between causal beliefs and covariation information (for overviews, see Ahn & Kalish, 2000; De Houwer & Beckers, 2002; Perales & Catena, 2006). The ***bottom-up*** approach assumes that people experience a causal link as a function of the associative weights (e.g. Shanks & Dickinson, 1987; Wasserman, Elek, Chatlosh, & Baker, 1993) or the statistical relationship (Cheng, 1997) between cues and outcomes. The ***top-down*** approach assumes that people possess an abstract knowledge of causality to detect a causal relation when presented with covariation data (Ahn, Kalish, Medin, & Gelman, 1995; Waldmann & Holyoak, 1992). Finally, causal Bayesian networks represent an approach to account for causal relations (Griffith & Tennenbaum, 2005; Waldmann, 2000). These networks are displayed through directed acyclic graphs in which the nodes represent the variables (types of events or states of the world) and the edges (arrows) represent the direct causal relations or probabilistic dependence between those variables (see also Waldmann et al., 2006). However, operating with a large number of variables, similarly to the present experiments, makes it difficult for these networks to identify the causal structure underlying data (e.g., the four causal candidates—i.e., cues—in our experiments would result in 16 possible models, without taking background causes or a priori likelihoods of these models into account).

There are also recent theoretical approaches that integrate the influence of empirical evidence as a function of causal mental models (Catena, et al., 1998; Lien & Cheng, 2000; Fugelsang & Thompson, 2003). They propose that previous causal beliefs do not represent an absolute filter to assess further covariation information (i.e., accepting only evidence that is in line with these beliefs) but as a framework to interpret new covariation information. Recent ***causal model theories of choice*** (Sloman & Hagmayer, 2006; Hagmayer & Sloman, 2009) extend this idea to decision making. Its underlying assumption is that people induce causal models by a decision problem and choice situation, thereby applying initial beliefs about such causal models. Causal knowledge might allow decision makers to constrain the countless number of cues that appear in a particular environment to a subset of cues that are more likely to have a high predictive value (Meder, Hagmayer & Waldmann, 2009). In this vein, causal beliefs can be perceived as hypotheses to be tested and updated with empirical data as a function of decisions (see also Koslowski, 1996; Koslowski & Masnick, 2002).

The current work aims to disentangle the differential influence of causal beliefs and empirical evidence on decision making and causal judgments, thereby applying the ***Belief Revision Model*** (BRM; Catena, et al., 1998). The BRM is an additive model that aims to integrate new statistical information into a cause-effect relationship. The integrative causal judgment ($\boldsymbol{J}_n$) stands for the measurement of belief updating. It consists of an additive function, which adds the prior causal belief ($\boldsymbol{J}_{n-1}$) to its discrepancy from the ***NewEvidence*** (see Appendix 3), multiplied with ***ß***, which codifies the reliability of the covariation evidence' origin or new information (Perales, et al., 2007):

$$\boldsymbol{J}_n = \boldsymbol{J}_{n-1} + \boldsymbol{ß}(\boldsymbol{NewEvidence} - \boldsymbol{J}_{n-1}). \tag{1}$$

Whether the reasoner holds a previous causal belief is reflected in a $\boldsymbol{J}_{n-1}$ value between '0' and '1'—whereas a value of '0' shows the absence of any a priori cause-effect beliefs. The reliability of the new evidence can also reach a value between '0' (for non-reliable information) and '1' (for very reliable information).

Applying the BRM to the current findings can explain differences in causal judgments, but also results for decision making. Decision making resembles the parameter ***NewEvidence*** (ΔD; Maldonado, Catena, Cándido, & Garcia, 1999) provided in the task. Participants had to select between two alternatives and four cues predicted the outcome (cues were either present or absent, and could predict the presence of the absence of the outcome). A weighted ΔD (***New Evidence***) calculated separately for each of the two alternatives correlates highly with mean selections in decision making. Positive correlations for alternative A, and negative correlations for alternative B indicate that participants applied the difference between these two ΔD to make their decisions.

To explain causal judgments, parameter values are different for medical and financial domains. In the medical domain, people hold strong causal beliefs for generative (i.e., a high $\boldsymbol{J}_{n-1}$) and low causal beliefs for preventive cues (i.e., a $\boldsymbol{J}_{n-1}$ around '0'), accompanied with low reliability (***ß***) for the new evidence provided in the task. In the financial domain, people hold weak causal beliefs (i.e., values of $\boldsymbol{J}_{n-1}$ below 0.5) for both generative and preventive cues, accompanied with high reliability (***ß***) of the new evidence. For participants in low judgment frequency group in the financial domain, the reliability of the new evidence increases—as these participants had no anchor of the initial causal judgment about generative and preventive cues. In the high judgment frequency groups of both domains, the BRM could also account for the current findings by using the values of the third causal judgments as parameters for $\boldsymbol{J}_{n-1}$.

Taken together, the present work demonstrates that people use causal judgments as an anchor classifying or interpreting new evidence in a two-alternative forced-choice including four predictive cues. Decision making reflects the parameter of the ***NewEvidence*** provided to the reasoner and represents a variable influencing a causal judgment. Naturally, the strength of causal beliefs and the perceived reliability of new evidence differ between domains and are parameters, which affect the causal judgment. A model like the BRM (Catena et al., 1998) integrates these parameters and serves as an elegant framework to account for the current findings.

Participants in our experiments held very strong causal beliefs in the medical domain, but they were susceptible to the empirical evidence in the financial domain. An explanation for this finding may be the perceived temporal variability of cue validities: In the medical domain, cues that were reliable in the past are very likely to continue being reliable in the future (for instance, the poisonousness of a substance will not fade over time; Müller et al., 2011). In the financial domain, however, it is very unlikely to find reliable and predictive cues—even the long term survival of a company may not be an indicator for its survival in the future (Ross Sorkin, 2008).

Future research could map out additional factors influencing causal beliefs or the reliability of new evidence. For instance, experts in certain domains (e.g., financial, medical) might hold stronger causal beliefs than university students who participated in the current experiments. This could affect the extent to which their causal beliefs serve as an anchor when making new causal judgments and decisions, as well as their susceptibility to new evidence. Further research could also address other domains as an influential factor on the strength of causal beliefs. For instance, stereotypes or prejudice resemble strong causal beliefs in the social domain: Once a person possess a stereotypic belief about a certain (out)group, new evidence often fails to be taken into account (Gill, 2004).

Conclusion

The current experiments demonstrated that (1) judgment frequency may lead to an integration of the empirical evidence experienced during a two-alternative forced-choice task (2) domain-specific information influences causal beliefs, which are stronger in the medical than in the financial domain, and (3) a theoretical model like BRM (Catena et al., 1998), which takes into account the reliability of the empirical evidence and the strength of a causal belief explains the current findings and disentangles the dissociation between decision making and causal judgments.

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Appendix 1

Cue	Preventive version	Generative version
	Medical domain	
Exercise	Regularly does exercise	Never does exercise
Daily diet	Vegetables and low fat food (e.g., whole grains, little meat)	Food high in calories and fat (e.g., white bread, French fries)
Amount of stress	Living without any stress	Living a stressful life
Alcohol consumption	Alcohol abstinence	Consuming high quantities of alcohol
	Financial domain	
The ***Financial Times*** offers a daily report about the stock market.	The latest report was promising	The latest report was negative
Vacancies or work dismissals can be a sign of a company's well-being.	The company has new vacancies	The company dismisses staff
The strength of the euro is directly related to the financial market and affects the value of shares.	There has been an increase in the strength of the euro	There has been a decrease in the strength of the euro
Companies normally publish a trimestral report about their effectiveness, gains and losses.	The trimestral report was positive	The trimestral report was negative

Note: Material used in Experiments 2 and 3: Generative and preventive versions of four cues that participants could use to determine which of two patients would be more likely to develop heart disease or which of two companies would be more likely to experience a decrease in their share price.

Independent naïve participants ($\boldsymbol{n}$=51) rated the extent to which generative or preventive cues generated or prevented the outcome on a scale from 10 (positive relationship) to -10 (negative relationship). Generative cues were judged to generate the outcome ($\boldsymbol{M}_{\text{Stock}}$=4.87;$\boldsymbol{M}_{\text{Heart}}$=5.36) and preventive cues were judged to prevent the outcome, $\boldsymbol{M}_{\text{Stock}}$=-3.85, $\boldsymbol{F}(4, 46)$=0.173, $\boldsymbol{p}$<.001;$\boldsymbol{M}_{\text{Heart}}$=-4.2, $\boldsymbol{F}(1, 46)$=0.19, $\boldsymbol{p}$<.001, respectively. There was no difference in perceived causal strength between domains (stock market vs. heart disease), neither for generative, $\boldsymbol{F}(4, 41)$=0.89, $\boldsymbol{p}$=.277, nor for preventive, $\boldsymbol{F}(4, 51)$=0.95, $\boldsymbol{p}$=.62, cues, respectively. No difference was observed in the perceived strength of the relatedness with the outcome among generative, $\boldsymbol{F}_{\text{Stock}}(3, 66)$=5.42, $\boldsymbol{p}$=.286; $\boldsymbol{F}_{\text{Heart}}$ (3, 66)=10.446, $\boldsymbol{p}$=.128, or preventive, $\boldsymbol{F}_{\text{Stock}}(3, 81)$=1.75, $\boldsymbol{p}$=.872; $\boldsymbol{F}_{\text{Heart}}(3, 81)$=12.036, $\boldsymbol{p}$=.424, cues, respectively.

Appendix 2

It is important to differentiate between our manipulation of the cue validity and the concept of contingency. The contingency between a candidate cause (cue, ***c***) and its effect (outcome, ***o***) is defined by $\Delta \boldsymbol{P_c} = \boldsymbol{P}(\boldsymbol{o}|\boldsymbol{c}) - \boldsymbol{P}(\boldsymbol{o}|\neg \boldsymbol{c})$,where $\boldsymbol{P}(\boldsymbol{o}|\boldsymbol{c})$ is the probability of ***o*** given the presence of ***c*** (i.e., validity of the cue, which was manipulated in the studies presented here) and $\boldsymbol{P}(\boldsymbol{o}|\neg \boldsymbol{c})$ is that probability given the absence of ***c***. In contingency terms, a positive $\Delta \boldsymbol{P_c}$ value refers to ***c*** as a ***generative*** or excitatory cause; a negative $\Delta \boldsymbol{P_c}$ value refers to ***c*** as a ***preventive*** or inhibitory cause; a ***c*** value around zero means that cue and outcome are unrelated (Lien & Cheng, 2000).

To meet the requirements for a decision task following Gigerenzer et al. (1999), we manipulated cue validity. To serve our interest in causal judgments, we also calculated the contingency values for each cue after the experiment. High-validity cues (i.e., 0.90) resulted in a contingency between 0.50 and 0.60; low-validity cues (i.e., 0.10) resulted in a contingency between 0.00 and –0.20 (mean contingency was –0.10, confirming that the cue had no relation to the outcome).

Appendix 3

The frequency information of ***NewEvidence*** is computed as weighted ΔD:

$$Ne\quad Eviden\quad e\quad \frac{w\quad w\quad w\quad w}{} \tag{2}$$

with a, b, c, and d representing each trial (computed as ΔP; a = cue and outcome; b = only cue; c = only outcome; d = neither cue nor outcome), whereas w_j stands for the weight of each trial type following always a > b $\lesseqgtr$ c > d (see Catena et al., 2008; Maldonado et al., 1999). Thereby, w_j has a value between ‘0’ and ‘1’.

SUMMARY AND CONCLUSION

Summary and Conclusion

The present thesis addresses an important problem in research about decision making and causal judgments, namely the influence of causal beliefs on these processes. Previous research has shown that people cannot and do not fully process all available information in the environment (Simon, 1990). To select and structure the information in their environment, researchers suggest that people apply mental models about cause-effect relationships to identify the most relevant cues (Tversky & Kahnemann, 1974; Waldmann, Hagmayer, & Blaisdell, 2006). Causal beliefs or prior experience can thereby boost decision making processes (Meder, Hagmayer, & Waldmann, 2008, 2009; Sloman & Hagmayer, 2006; Garcia-Retamero, Wallin & Diekman, 2007). However, causal beliefs can also interfere with the accurate evaluation of new empirical evidence resulting in a neglect of contradictive information (Alloy & Tabachnik, 1984; Fugelsang, Stein, Green, & Dunbar, 2004).

The present studies provide several novelties to measure the influence of causal beliefs in decision making and causal judgments. First, this series of experiments applies for the first time a two alternative-forced choice-task including four predictive cues, which differ in causality and validity. This complex experimental design allows to investigate perceived differences in decisions and causal judgments when (1) causal vs. neutral cues predict the outcome (in Garica-Retamero, Müller, Catena, & Maldonado, 2009, see chapter 1; Müller, Garcia-Retamero, Cokely, & Maldonado, in press, see chapter 2) and when (2) preventive vs. generative cues predict the outcome (Müller, Garcia-Retamero, Galesic, & Maldonado, submitted, JEP:A, see chapter 3; Müller, Garcia-Retamero, Catena, Galesic, Perales, & Maldonado, submitted, QUEP, see chapter 4).

Second, the thesis compares the influence of causal beliefs in decision making and causal judgments in different domains. Most research on judgment and decision making covers only single domain settings, but generalizes results to cognitive processes in other domains. The findings of Müller, et al. (submitted, see also chapter 3) indicate differences between domains and suggest limiting the validity of such results to the domain-specific environment of the particular experiment.

Finally, the thesis tries to map differences between decisions and causal judgments, which are often mentioned interchangeably. The findings in Müller, et al. (in press, see chapter 2) and Müller, et al. (submitted, see chapter 3) indicate a substantial dissociation between these two processes. The final chapter of the thesis (chapter 4) tries to theoretically account for this dissociation applying the ***Belief Revision Model***. The model integrates the reliability of the new evidence—which is more important in decision making—and the strength of a causal belief—which is more important in causal judgments.

This summary is structured as follows: First, it provides a brief overview of the presented studies. Second, it offers an interpretation of these empirical findings placing them into a general theoretical framework. Finally, it offers ideas for future research to overcome the possible limitations of the present work.

Synopsis of the studies

Garcia-Retamero, et al. (2009; chapter 1) analyze the relative influence of causal beliefs and empirical evidence (i.e., cue validities) on causal judgments and decision making. The results reveal that the impact of causal beliefs and empirical evidence depends on previous experience (or pre-training). While participants without any pre-training relied mainly on their causal beliefs—favoring causal over neutral cues—, pre-training with causal cues led to a clear preference for the causal high-validity cues. When participants received pre-training with neutral cues (i.e., cues which are not causally linked to the criterion), their decisions were primarily based on the empirical evidence, regardless of whether cues were causal or neutral. These findings suggest that participants rely on their causal beliefs by default.

However, pre-training with neutral cues increases the sensitivity to the validity information, independent of any causal information.

Müller, et al. (in press; chapter 2) extends the previous research with the attempt to overcome participants' neglect of the empirical evidence and thereby identifying mechanisms underlying decision making. Results show that greater amounts of empirical evidence (i.e., en increased amount of trials) with highly discriminative cues also lead to a reliance on empirical evidence in decision making and causal judgments. Additionally, this study indicated some dissociation between causal judgments and decision making—showing that the impact of causal beliefs is stronger in causal judgments, whereas decisions seemed to be based on the empirical evidence. Participants used instructions (causal vs. neutral) as an anchor to make decisions and causal judgments. This anchor did not remain stable when participants accumulated more experience: By increasing the number of trials and the difference between cue validities, people improved the integration of empirical evidence in decision making and judgments.

Mülller et al. (submitted, chapter 3) demonstrates that domain-specific information about the decision cues and the outcome crucially affects the influence of causal beliefs in decision making and causal judgments. Three experiments show that causal beliefs influence decisions and causal judgments to a greater extent in the medical than in the financial domain. In the ***medical domain***, causal beliefs had a strong influence on causal judgments, independently of the experienced cue validities during the decision task. There was also an effect of causal beliefs in decision making when cues revealed domain specific information. In the ***financial domain***, decisions and causal judgments were mainly guided by and adapted to the empirical evidence provided via cue validities.[15]

[15] When instructions provided abstract information about the cues, causal beliefs had a transitory effect on causal judgments in the medical domain.

Consequently, findings indicated a double dissociation: (1) Between domains: Causal beliefs were stronger in the medical than in the financial domain and (2) between decisions and causal judgments (in line with Müller et al., in press; chapter 2). When participants received abstract information about cues, decisions adapted to the cue validities, whereas causal judgments differed according to the influence of causal beliefs between domains—indicating an effect of causal beliefs in the medical but not the financial domain. In both domains, this dissociation disappeared when participants received domain-specific information about cues that predicted the outcome. In the medical domain, more detailed information led to a reliance on causal beliefs primarily, whereas more detailed information in the financial domain led to a reliance on the empirical evidence.

The differential influence of domain-specific causal information on these processes might be related to the perceived temporal variability of cue validities within a domain, which in turn may affect the strength of a causal belief. Finally, findings highlight the importance to be careful in generalizing results that were obtained within a single domain to cognitive processes in other domains. The authors recommend limiting such results to the domain-specific environment until further evidence is available.

Finally, Müller et al. (submitted, chapter 4) maps the interplay between the (in)flexibility of causal beliefs and the frequency-of-judgment effect (see Catena, Maldonado, & Cándido, 1998) on causal judgments and decision making. Results show that judgment frequency leads to an integration of the empirical evidence which participants experienced throughout the decision task. This finding is similar to Müller, et al. (in press; chapter 2), where an increase in the amount of decision trials led to a reliance on the empirical evidence in decisions and causal judgments. In line with Müller et al. (submitted, chapter 3), there was also an influence of domain-specific information on causal beliefs, which were stronger in the medical than in the financial domain—independently of whether participants received a monetary compensation for their participation. Similarly to previous work (Müller et al., submitted; chapter 4), we observed a double dissociation: (1) Between domains indicating a strong influence of causal beliefs in the medical domain but not in the financial domain, and (2) between decisions and causal judgments—showing a stronger influence of cue validities on decision making than on causal judgments. Finally, this study offers a theoretical explanation for the dissociation between decisions and causal judgments, thereby underlining the utility to include both empirical evidence and causal beliefs when explaining decision making and causal judgments.

Conclusion

The current findings provide converging evidence about the influence of previous causal beliefs in decision making and causal judgments (see also Hagmayer & Sloman, 2009; Lagnado, Waldmann, Hagmayer, & Sloman, 2007). Causal beliefs might allow decision makers to reduce the countless number of cues that appear in a particular environment to a subset of cues with a highly predictive value. Consequently, causal beliefs might act as hypotheses that are tested and updated with empirical data—the confirmation or disconfirmation of these beliefs depends on the strength of previous causal beliefs and the experience with the selected cues in the environment (Koslowski & Masnick, 2002; Meder et al., 2008, 2009).

In the same vein, the ***Belief Revision Model*** (BRM, Catena, et al., 1998) suggests that causal beliefs act as an anchor that determines the influence of new empirical evidence (Catena, Maldonado, Perales, & Cándido, 2008; see Fugelsang & Thompson, 2003; Lien & Cheng, 2000 for other attempts). This additive model integrates new covariation information into a cause-effect relationship (see also Hogarth & Einhorn, 1992 for an earlier approach). Belief updating is thereby processed through the strength of the prior belief and the "reliability" of the new evidence (Perales, Catena, Maldonado, & Cándido, 2007; also "plausibility," see Fugelsang & Thompson, 2003). Applying the BRM to the current findings can explain causal judgments and also decision making: Decisions are nearly exclusively based on the new evidence that participants experience during the task, whereas causal judgments are rather based on the strength of the previous causal belief. Weak causal beliefs increase the permeability and reliability of empirical information. Strong causal beliefs, however, may interfere with the new evidence and lead to a decrease in the perceived reliability of the empirical information. Consequently, this theoretical approach can account for the current findings and differential influence of causal beliefs depending on the domain (chapter 3; chapter 4), previous experience (or pre-training, see chapter 1; chapter 2), or judgment frequency (see chapter 4). In any case, a theoretical model explaining causal learning and judgments must take into account the differential influence of cognitive-based processes (such as prior knowledge and causal beliefs) and empirical evidence (such as cue validities and covariation information).[16]

Limitations and future research

The current work is an attempt to map the influence of causal beliefs and perceived reliability of new evidence in decisions and causal judgments. The studies presented here give also rise to several lines of future research. First, participants in all studies were university students and research is needed to replicate these findings in natural settings. For instance one could compare causal beliefs in experts and novices. Experts in certain domains (e.g., financial, medical) might hold stronger beliefs than when participants are university students (as in the

[16] Alternatively, these results could also be considered from a Bayesian point of view (Griffiths & Tenenbaum, 2005). In their support model, Griffith and Tenenbaum (2005) act on the assumption that a causal judgment reflects the reasoner's degree of certainty linking cause and effect. The existence of four causal candidates in our experiments would result in 16 possible models – excluding background causes and the possibility of a priori likelihoods of these models. Although it may be possible, Bayesian models have not yet been developed to handle this level of complexity.

current experiments). The everyday work of a doctor or broker involves frequent decisions and judgments – it would be a challenge to map the influence of judgments as an anchor or whether these experts are similarly susceptible to new evidence.

Second, several other relevant domains of life may be affected by the influence of causal beliefs (e.g., moral beliefs, social relationships, or the influence of prejudice). Stereotypes, for instance, resemble commonly shared causal beliefs about certain social groups and their attributes, roles, or behavior. Once a person possesses a stereotypic belief about a certain group, new evidence often fails to be taken into account (Gill, 2004). In a similar vein, different target groups of people may hold different causal beliefs about the social world.

Third, the influence of individual differences should not be underestimated. Individual differences in participants' abilities (e.g., working-memory capacity) might play a crucial role in the reliance on causal beliefs or when encoding empirical evidence, thereby influencing the search strategy of participants in the decision task (Cokely & Kelley, 2009). In the same vein, it would be important to map participants' search process. Although an exhaustive cue search might have led to the best performance in the decision task, the differential influence of the search process on decisions and causal judgments remains open for future research.

Taken together, this thesis provides converging evidence for the influence of causal beliefs in decision making and causal judgments. It also highlights the need of a theoretical framework—like the BRM—which accounts for both causal beliefs and empirical evidence to explain these processes. Finally, despite empirical results and theoretical accounts, the present studies show that this complex topic still leaves avenues for future research which yet have to be challenged.

RESUMEN Y CONCLUSIÓN

Resumen y conclusión

La presente tesis doctoral trata un problema importante en la investigación sobre la toma de decisiones y juicios de causalidad, como es la influencia de las creencias causales en esos procesos. Investigaciones anteriores han demostrado que la gente no puede procesar toda la información disponible en el medio ambiente (Simon, 1990). Para seleccionar y estructurar la información en su entorno, los investigadores sugieren que las personas se aplican modelos mentales acerca de las relaciones causa-efecto para identificar las claves más relevantes (Tversky y Kahnemann, 1974; Waldmann, Hagmayer, y Blaisdell, 2006). Por tanto, la creencias causales, más allá de la experiencia directa, pueden mejorar la toma de decisiones (Meder, Hagmayer, y Waldmann, 2008, 2009, Sloman y Hagmayer, 2006; García-Retamero, Wallin y Diekman, 2007). Sin embargo, las creencias causales también pueden interferir con la evaluación precisa de la nueva evidencia empírica resultando en una negligencia de la información contradictoria (Alloy y Tabachnik, 1984; Fugelsang, Stein, Green, y Dunbar, 2004).

Los estudios actuales ofrecen varias novedades en el estudio de la influencia de las creencias causales en la toma de decisiones y juicios de causalidad. En primer lugar, esta serie de experimentos aplica por primera vez una tarea de comparación entre pares de elección forzosa, incluyendo cuatro claves predictivas. Este diseño experimental complejo permite investigar las diferencias en la toma de decisiones y en los juicios causales cuando: (1) claves causales vs claves neutrales predicen las consecuencias de la decisión (en Garcia-Retamero, Müller, Catena, y Maldonado, 2009, véase capítulo 1; Müller, García-Retamero, Cokely, y Maldonado, en prensa, véase capítulo 2), (2) claves preventivas vs generativas predicen esas mismas consecuencias (Müller, García-Retamero, Galesic, y Maldonado, enviado a publicación: JEPA, véase capítulo 3; Müller, García-Retamero, Catena, Galesic, Perales, y Maldonado, enviado a publicación: QUEP; véase capítulo 4).

En segundo lugar, la tesis compara la influencia de las creencias causales en la toma de decisiones y juicios de causalidad en diferentes dominios. La mayoría de las investigaciones sobre la toma de decisiones juicios causales sólo se refieren a un dominio único, normalmente neutro, pero generaliza los resultados a procesos cognitivos en otros dominios. Los resultados de Müller y otros (enviado, JEP:A, véase también capítulo 3) y Müller y otros (enviado, QUEP, véase también capítulo 4) indican diferencias entre dominios y sugieren limitar la validez de los resultados experimentales al medio ambiente de dominio específico de cada experimento particular. Lo cual sugiere además, la necesidad de nuevas perspectivas de investigación en el área de la toma de decisiones y la atribución de causalidad.

Por último, la tesis trata de las diferencias entre los factores que afectan a las decisiones y los juicios de causalidad, que se mencionan a menudo de manera intercambiable. Los resultados de Müller, y otros (en prensa, véase capítulo 2) y Müller y otros (enviado, JEP:A , véase capítulo 3) indican una clara disociación entre estos dos procesos en función del efecto de las creencias causales previas y de la validez empírica de las claves. El último capítulo de la tesis (Müller, y otros, enviado, QUEP, véase capítulo 4) intenta una aproximación teórica a la explicación de esta disociación basada en el modelo de revisión de creencias que permite integrar la fiabilidad de la evidencia empírica, mas importante en el proceso de decisión, con la fuerza de las creencias causales, más importantes en el proceso de atribución causal.

Este resumen está estructurado de la siguiente manera: En primer lugar, se ofrece una breve descripción sobre los estudios presentados. En segundo lugar, interpreta estos resultados empíricos dentro de un marco teórico general. Por último, ofrece ideas para investigaciones futuras que permitan superar las posibles limitaciones del presente trabajo.

Sinopsis de los estudios

En el primer trabajo, (García-Retamero, y otros, 2009, capitulo 1) se analiza la influencia relativa de las creencias causales y la evidencia empírica (es decir, la validez de las claves) en los juicios de causalidad y toma de decisiones. Los resultados revelan que el impacto de las creencias causales y la evidencia empírica dependen de la experiencia previa (o pre-entrenamiento). Cuando los participantes no recibieron ningún tipo de pre-entrenamiento, sus decisiones y juicios causales dependían sobre todo de sus creencias causales obtenidas probablemente a lo largo de su experiencia previa con dichas claves—favoreciendo las claves causales sobre claves neutrales. De hecho, un pre-entrenamiento con las claves causales, resulto también en una clara preferencia y mayor influencia de las claves causales, sobre todo cuando además su validez era alta. Sin embargo, cuando los participantes recibieron un pre-entrenamiento con claves neutrales (es decir, claves que no están causalmente relacionadas con el criterio), sus decisiones se basaron principalmente en la evidencia empírica, independientemente de sus creencias previas. Estos resultados sugieren que los participantes confían en sus creencias causales de forma predeterminada. Sin embargo, un pre-entrenamiento con claves neutrales aumenta la sensibilidad a la evidencia empírica, independiente de cualquier información causal, posiblemente porque son capaces de focalizar la atención en la covariación más que en la naturaleza de las claves.

Müller y otros (en prensa, capitulo 2) ampliaron esta investigación con el objetivo de analizar más posibilidades de superar la negligencia de la evidencia empírica a favor de las creencias previas. Los resultados mostraron que una mayor cantidad de entrenamiento (es decir, incrementando los ensayos de la tarea de decisiones) con claves muy discriminativas, también resulta en un mayor peso de la evidencia empírica en las decisiones y los juicios causales. Además, este estudio mostró la existencia de una cierta disociación entre los juicios de causalidad y la toma de decisiones—mostrando que el impacto de las creencias de causales es más fuerte en los juicios de causalidad, mientras que las decisiones parecen depender más de la evidencia empírica o validez objetiva de las claves. Los participantes utilizaron las instrucciones sobre las claves (causales vs. neutrales) como un ancla para tomar decisiones y para los juicios de causalidad. Este anclaje no se mantuvo cuando los participantes acumularon más experiencia; es decir, aumentando el número de los ensayos y la diferencia entre la validez de las claves resultaba en una mayor ponderación de la evidencia empírica en la toma de decisiones y juicios.

Mülller, y otros (enviado, JEP:A, capitulo 3) demuestran que la información específica del dominio sobre las claves y sus consecuencias tiene un efecto fundamental en relación a la influencia de las creencias causales en la toma de las decisiones y los juicios de causalidad. Tres experimentos muestran que las creencias causales influyen en las decisiones y los juicios de causalidad en mayor medida en el dominio médico que en el dominio financiero. En el dominio médico, las creencias causales tuvieron una fuerte influencia sobre los juicios causales, independientemente de la validez de las claves y también se encontró cierta influencia de las creencias causales en la toma de decisiones, dentro de este dominio. Sin embargo, en el dominio financiero, las decisiones y los juicios de causalidad eran guiados principalmente por la evidencia empírica proporcionada a través de la validez de las claves.[17]

En consecuencia, los resultados indicaron una doble disociación. (1) Entre los dominios: las creencias causales eran más fuertes en el dominio médico que en el dominio financiero y (2) entre las decisiones más sensibles a la evidencia empírica independientemente de las creencias causales, y los juicios de causalidad, más sensibles a las creencias previas independientemente de la validez objetiva de las claves, sobre todo en el dominio médico (véase también Müller et al, en prensa, capítulo 3). Así, cuando los participantes recibieron información abstracta, las decisiones se adaptaron exclusivamente a

[17] Cuando las instrucciones proporcionaron información abstracta sobre las claves (Experimento 1), las creencias causales en el ámbito financiero tuvieron un efecto transitorio sobre los juicios de causalidad.

la validez de las claves, mientras que los juicios causales difirieron entre dominios—indicando un efecto de creencias causales en el dominio medico, pero no en el dominio financiero. En ambos dominios, esta disociación desapareció cuando los participantes recibieron la información específica del dominio sobre claves en la tarea. En el dominio médico, la información más detallada llevó a una dependencia de las creencias causales, mientras que la información más detallada en el ámbito financiero no parce tener el mismo efecto y las decisiones y juicios causales se basaron en la evidencia empírica, independiente de su contenido causal.

La influencia diferencial de la información causal específica de cada dominio podría estar relacionada con la percibida variabilidad temporal de la validez de las claves dentro de un dominio—que puede afectar a la fuerza de una creencia causal. Por último, las conclusiones destacan la importancia de tener cuidado al generalizar los resultados que se obtienen en un único dominio a los procesos cognitivos en otros dominios. Los autores recomiendan limitar dichos resultados al entorno específico del dominio del experimento hasta que se disponga de más resultados de otros dominios.

Por último, Müller, y otros (enviado, QUEP, capitulo 4) investigan la interacción entre la (in)flexibilidad de las creencias causales y el efecto de la frecuencia de juicios (véase Catena, Maldonado y Cándido, 1998) en los juicios de causalidad y la toma de decisiones. Los resultados muestran que la frecuencia del juicio lleva a una mayor influencia de la evidencia empírica que los participantes experimentaron durante de la tarea de decisión. Este resultado es similar al de Müller, y otros (en prensa, capítulo 2), donde un aumento en la cantidad de ensayos de la tarea de decisiones llevó a resultados similares sobre la influencia de la evidencia empírica en la toma de decisiones y juicios causales. Los resultados también confirmaron los resultados previos dado que la información específica del dominio determinaba la influencia de las creencias causales, más fuertes en el dominio médico que en el financiero. Este efecto se produjo independientemente de la compensación monetaria recibida por los participantes por su participación.

En línea con los otros trabajos (Müller y otros, enviado JEP:A, capítulo 3), se observó una doble disociación: (1) Entre los dominios indicando una fuerte influencia de las creencias causales en el dominio médico, pero no en el financiero, y (2) entre las decisiones y juicios de causalidad—mostrando una mayor influencia de la validez de las claves en la toma de decisiones que en los juicios de causalidad. Por último, este estudio ofrece una explicación teórica de la disociación entre las decisiones y juicios causales basada en el modelo de revisión de creencias, subrayando la utilidad de incluir tanto el cómputo de la evidencia empírica, como la fuerza de las creencias causales previas para explicar la toma de decisiones y juicios de causalidad.

Conclusiones

Los actuales resultados proporcionan evidencia convergente sobre la influencia de las creencias causales previas en la toma de decisiones y los juicios de causalidad (véase también Hagmayer y Sloman, 2009; Lagnado, Waldmann, Hagmayer, y Sloman, 2007). Las creencias causales podrían permitir reducir el número incontable de las claves que aparecen en un entorno especial, para detectar claves con un alto valor predictivo a la hora de tomar decisiones. En consecuencia, las creencias causales pueden actuar como hipótesis o heurísticos que se prueban y se actualizan con los datos empíricos. La confirmación o negación de estas creencias depende de la fuerza de las creencias causales previas, que depende también del tipo de domino, más allá de la mera experiencia con las claves seleccionadas en el medio ambiente (Koslowski y Masnick, 2002; Meder y otros, 2008, 2009).

En este sentido, es importante reconocer que el modelo de la revisión de creencias (BRM, Catena, et al, 1998) sugiere que las creencias causales actúan como un ancla que determina la influencia de la nueva evidencia empírica (Catena, Maldonado, Perales, y Cándido, 2008; véase Fugelsang y Thompson, 2003; Lien y Cheng, 2000 para otros intentos). Este modelo aditivo integra la nueva información sobre la covariación de una relación causa-efecto (véase también Hogarth y Einhorn, 1992), de forma que la actualización de la creencia depende de la integración de la información sobre covariación con la fuerza de la creencia previa, en función de la "fiabilidad" otorgada a las nueva evidencia empírica (Perales, Catena, Maldonado y Cándido, 2007; también "plausibilidad", véase Fugelsang y Thompson, 2003). De esa forma, podrían explicarse los resultados actuales, asumiendo que las decisiones dependen casi exclusivamente de la nueva evidencia, mientras que los juicios de causalidad dependerían más del proceso de integración con la fuerza de las creencias previas. Este supuesto explicaría los resultados encontrados y la disociación entre ambos procesos en el dominio medico, donde la fuerza de las creencias es mayor; pero no en el dominio financiero, donde las creencias previas apenas tienen ningún tipo de efecto (véase Müller y otros, enviado, QUEP; capítulo 4). Por tanto, las creencias causales débiles aumentan la permeabilidad y la fiabilidad de la información empírica; mientras que fuertes creencias causales pueden interferir con la nueva evidencia y llevar a una disminución en la percepción de fiabilidad de la información empírica (ver resultados en el dominio médico en Müller y otros, enviado, QUEP; capítulo 4). En cualquier caso, un modelo teórico capaz de explicar el aprendizaje causal y la toma de decisiones debe tener en cuenta la influencia diferencial de los procesos cognitivos (como los conocimientos previos y creencias causales) y la evidencia empírica (como la validez de de las claves e información de covariancia) en ambos tipos de procesos. [18]

[18] Alternativamente, estos resultados también se podría considerar desde un punto de vista bayesiano (Griffiths

Limitaciones e investigación futura

El presente trabajo es un intento para investigar la influencia de las creencias causales y la percepción de la fiabilidad de la evidencia empírica en decisiones y juicios causales. Los estudios presentados aquí también sugieren nuevas líneas de investigación futura. En primer lugar, los participantes en todos los estudios fueron estudiantes universitarios y por lo tanto, es necesario replicar esta investigación a un ambiente natural. Por ejemplo se podría comparar las creencias causales de expertos y novatos. Es difícil predecir si los expertos en dominio específicos (por ejemplo, el dominio médico o financiero) pueden mantener creencias más o menos fuertes que cuando los participantes son estudiantes universitarios (como en los experimentos actuales). El trabajo diario de un médico o consejero financiero involucra decisiones y juicios frecuentes - sería interesante si estos expertos usan los juicios como un ancla o si son igualmente susceptibles a evidencia nueva.

En segundo lugar, otros dominios relevantes de la vida diaria pueden ser afectados por la influencia de las creencias causales (por ejemplo, las creencias morales, las relaciones sociales, o la influencia de los prejuicios). Los estereotipos, por ejemplo, parecen similares a las creencias causales compartidos acerca de ciertos grupos sociales y sus atributos, funciones, o su comportamiento. Una vez que una persona posee una creencia estereotipada acerca de un grupo determinado, cualquier nueva evidencia a menudo no se tiene en cuenta (Gill, 2004). En este sentido, diferentes grupos de personas pueden tener diferentes creencias causales acerca del mundo social y por tanto ser susceptibles de cambio mucho más difícilmente.

En tercer lugar, las diferencias individuales podrían tener también influencia en los procesos de la toma de decisión y la atribución de causalidad. Las diferencias individuales en

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y Tenenbaum, 2005). En su modelo de apoyo, Griffith y Tenenbaum (2005) actúan sobre la presunción de que la sentencia refleja el grado de causalidad del razonador de la causa que une la seguridad y el efecto. La existencia de cuatro candidatos causales en nuestros experimentos se traduciría en 16 modelos posibles - excluyendo las causas de fondo y la posibilidad de probabilidades a priori de estos modelos. Aunque puede ser posible, los modelos bayesianos aún no se han desarrollado para manejar este nivel de complejidad.

habilidades cognitivas (por ejemplo, la capacidad de memoria de trabajo) podrían desempeñar un papel crucial en la adherencia a las creencias causales o en la codificación de la evidencia empírica—lo que pueden influir además en las estrategias de búsqueda de información sobre las claves de los participantes en la tarea de decisiones (Cokely y Kelley, 2009). En el mismo sentido, sería importante investigar el proceso de búsqueda de información. Aunque una búsqueda exhaustiva haya resultado casi la única estrategia para una mejor ejecución en la tarea de decisión presentada, analizar los factores que podrían influir en dicha búsqueda es una tarea pendiente de investigación futura, así como la posible influencia en la toma de decisiones y detección de relaciones causales.

En suma, la investigación actual es solo un primer paso en el estudio de las relaciones complejas entre creencias causales y evidencia directa en la elección entre alternativas y los juicios de causalidad. Por ello, más allá de los resultados experimentales y de sus posibles explicaciones teóricas, los estudios actuales demuestran que este es un tema complejo que deja vías abiertas a futuras investigaciones en un campo tan importante como la toma de decisiones y la inferencia de causalidad en nuestra vida diaria.

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