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11 Unintentional Influences in Intentional Impression Formation[1]

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A substantial body of research suggests that perceivers spontaneously draw inferences from observed behaviors even when they do not have the intention to form a social impression. Such unintentional inferences have been found to give rise to impressions of other people's traits (i.e., spontaneous trait inference; see Uleman et al., 1996) and goals (i.e., spontaneous goal inference; see Moskowitz & Olcaysoy Okten, 2016). For example, when learning that Avery received an A on a math exam, people may spontaneously infer that Avery is smart; and when learning that Alex donated $100 to a local food bank, people may spontaneously infer that Alex had the goal to help. Although these impressions can be the result of intentional processes, the notion of spontaneous inference suggests that they may also arise from unintentional processes.

The current chapter reviews research on a related, yet conceptually distinct phenomenon: unintentional influences in intentional impression formation. The central focus of our review is on the finding that mere co-occurrence of stimuli can produce evaluative responses that are diametrically opposite to intentionally formed impressions based on the particular relation between the co-occurring stimuli. This phenomenon is similar to the concept of spontaneous inference, in that it involves unintentional effects in impression formation. However, it is different from the concept of spontaneous inference, in that it arises in contexts where people do have the intention to form an impression. Another important difference is that, while prior research on spontaneous inference has predominantly focused on impressions with specific semantic content (e.g., intelligent vs. unintelligent), evidence for unintentional influences in intentional impression formation is primarily coming from studies on broad evaluative impressions (e.g., good vs. bad).[2]

In the first part of this chapter, we illustrate the differential effects of mere co-occurrence and relational information in impression formation. Expanding on this distinction, the second part reviews evidence for unintentional influences in intentional impression formation, as reflected in dissociative effects of mere co-occurrence and relational information on implicit and explicit measures. The third part describes a novel approach to identify effects of mere

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co-occurrence and relational information via formal modeling. In the fourth part, we discuss competing theoretical explanations for unintentional influences in intentional impression formation and evidence regarding the impact of theoretically derived moderators that make such influences more or less likely to occur. In the final part, we discuss broader implications of the reviewed research for impression formation.

Effects of Mere Co-occurrence and Relational Information

Unintentional influences in intentional impression formation can occur in various forms, as demonstrated by classic research on halo and priming effects in impression formation. In the current chapter, we focus on a more recent line of work suggesting that evaluative responses to an object may be jointly influenced by (1) the mere co-occurrence of the object with a pleasant or unpleasant stimulus (e.g., mere co-occurrence of object A and negative event B) and (2) the object's particular relation to the co-occurring stimulus (e.g., object A starts vs. stops negative event B). To illustrate the difference between mere co-occurrence and relational information, imagine a hypothetical health campaign that aims to promote the use of sunscreen with the message that sunscreen protects against skin cancer. To the extent that people understand and accept this message, the presented information about the relation between sunscreen and skin cancer should lead to a positive response to sunscreen. Yet, in line with the notion of *evaluative conditioning* (EC), the same message could also lead to a negative response to sunscreen due to the mere co-occurrence of *sunscreen* with the negative concept *skin cancer* in the message. EC is commonly defined as the change in the evaluation of a conditioned stimulus (CS) due to its pairing with a positive or negative unconditioned stimulus (US; see De Houwer, 2007). In our thematic example, the mere pairing of sunscreen (CS) and skin cancer (US) in the message may produce an EC effect on evaluative responses to sunscreen that is diametrically opposite to the effect that can be expected if recipients comprehend and accept the causal relation of sunscreen and skin cancer described in the message. Whereas mere co-occurrence should lead to a negative response to sunscreen, relational information should lead to a positive response to sunscreen.

Conceptually, the relation of an object and a co-occurring stimulus can be described as *assimilative* when it suggests an evaluative response to the object that is in line with the valence of the co-occurring stimulus (e.g., smoking causes lung cancer). Conversely, the relation of an object and a co-occurring stimulus can be described as *contrastive* when it suggests an evaluative response to the object that is opposite to the valence of the co-occurring stimulus (e.g., sunscreen prevents skin cancer). At the operational level, unintentional influences in intentional impression formation can be inferred when the following three conditions are met: (1) a given object has a contrastive relation to a positive or negative stimulus, (2) people intentionally use the object's contrastive relation to the co-occurring stimulus in forming an impression of the object, and (3) evaluative responses to the object are nevertheless influenced by its mere co-occurrence with the stimulus. To the extent that all three conditions are met, the effect under Point 3 can be interpreted as unintentional influence in intentional impression formation. For example, a message stating that sunscreen protects against skin cancer can be said to have an unintentional influence in intentional impression formation when message recipients intentionally form a positive impression of sunscreen in response to the message, but nevertheless show a negative response to sunscreen due to the mere co-occurrence of sunscreen and skin cancer in the message. In the following sections, we review empirical evidence for unintentional influences in intentional impression formation in terms of these three defining characteristics.

Evidence in Research Using Implicit and Explicit Measures

Preliminary evidence for unintentional influences in intentional impression formation comes from several studies using a combination of implicit and explicit measures to identify effects of mere co-occurrence and relational information. The central finding in this line of work is that implicit measures (e.g., implicit association test; evaluative priming task; for an overview, see Gawronski & De Houwer, 2014) sometimes reflect effects of mere co-occurrence even when explicit measures (e.g., evaluative rating scales) reflect effects of relational information.

In the first demonstration of such dissociative effects, Moran and Bar-Anan (2013) presented participants with sequences of images and sounds. Each sequence started with an image of one alien creature, followed by either a pleasant or an unpleasant sound (i.e., pleasant melody or unpleasant scream), followed by an image of a different alien creature. Participants were told that, depending on their position in the sequence, some aliens would start the following sound whereas other aliens would stop the preceding sound. Participants were asked to form an impression of the alien creatures based on the presented information. After the impression formation task, evaluative responses to the alien creatures were measured with an explicit and an implicit measure (i.e., implicit association test; see Greenwald et al., 1998). Whereas responses on the explicit measure reflected the particular relation of the aliens to the sounds, responses on the implicit measure reflected the mere co-occurrence of aliens and sounds regardless of their relation. Specifically, on the explicit measure, participants showed more favorable judgments of aliens that started pleasant sounds compared with aliens that stopped pleasant sounds. Conversely, participants showed less favorable judgments of aliens that started unpleasant sounds compared with aliens that stopped unpleasant sounds. In contrast, on the implicit measure, participants showed more favorable responses to aliens that co-occurred with pleasant sounds compared with aliens that co-occurred with unpleasant sounds, regardless of whether the aliens started or stopped the sounds.

Similar findings were obtained by Hu et al. (2017, Experiments 1 and 2). Participants were presented with image pairs involving pharmaceutical products and positive or negative health conditions (e.g., healthy hair, skin rash). Half of the participants were told that the pharmaceutical products cause the depicted health conditions; the other half was told that the pharmaceutical products prevent the depicted health conditions. Participants were asked to form an impression of the pharmaceutical products based on the presented information. After the impression formation task, evaluative responses to the pharmaceutical products were measured with an explicit and an implicit measure (i.e., evaluative priming task; see Fazio et al., 1995). Consistent with Moran and Bar-Anan's (2013) results, Hu et al. found that responses on the explicit measure reflected the relation between the pharmaceutical products and the depicted health conditions. In contrast, responses on the implicit measure reflected the mere co-occurrence of the products with the depicted health conditions regardless of their relation. Specifically, on the explicit measure, participants showed more favorable judgments of products that caused positive health conditions compared with products that prevented positive health conditions. Conversely, participants showed less favorable judgments of products that caused negative health conditions compared with products that prevented negative health conditions. In contrast, on the implicit measure, participants showed more favorable responses to products that co-occurred with positive health conditions than products that co-occurred with negative health conditions, regardless of whether the products caused or prevented the health conditions.

The findings by Moran and Bar-Anan (2013) and Hu et al. (2017) are consistent with the notion of unintentional influences in intentional impression formation. When the focal objects had a contrastive relation to a co-occurring stimulus, evaluative responses on implicit measures were influenced by mere co-occurrence, although responses on explicit measures reflected the intentional use of relational information in forming impressions of the focal objects. However, a more exhaustive review of the available evidence suggests that unqualified co-occurrence effects on implicit measures are not a ubiquitous outcome (see Kurdi & Dunham, 2020). Although some studies found mere co-occurrence effects on implicit measures that remained unqualified by relational information (e.g., Hu et al., 2017, Experiments 1 and 2; Moran & Bar-Anan, 2013), other studies found attenuated co-occurrence effects when the co-occurring stimuli had a contrastive relation (e.g., Zanon et al., 2012; Zanon et al., 2014). Yet, other studies found a full reversal of mere co-occurrence effects in cases involving contrastive relations (e.g., Gawronski et al., 2005; Hu et al., 2017, Experiment 3), suggesting that intentional processes completely overrode unintentional effects of mere co-occurrence. Together, these mixed findings suggest that the relative impact of mere co-occurrence and relational information on implicit measures may depend on specific conditions.

To date, there is empirical evidence for two moderators that seem to influence mere co-occurrence effects on implicit measures in the presence of contrastive relational information. First, Hu et al. (2017) found dissociative effects of mere co-occurrence and relational information on implicit and explicit measures only when the relational information was provided before the impression formation task and this information was consistent for all of the presented target stimuli (i.e., all of the pharmaceutical products either caused or prevented the depicted health conditions; see Experiments 1 and 2). However, when relational information was provided during the impression task and the specific relations varied on a trial-by-trial basis, both implicit and explicit measures were influenced by relational information without showing any effect of mere co-occurrence (Experiment 3). Second, Moran et al. (2015) found stronger mere co-occurrence effects on an implicit measure when participants were instructed to memorize the co-occurrence of the stimuli than when they were asked to form an impression of the target objects. However, memorization instructions also eliminated the effect of relational information on an explicit measure, which was influenced by mere co-occurrence instead of relational information under memorization conditions. Although these results suggest that effects of mere co-occurrence and relational information are goal-dependent, it is worth noting that the critical dissociation between implicit and explicit measures replicated under impression-formation instructions. In this case, the implicit measure was influenced by mere co-occurrence, while the explicit measure reflected the intentional use of relational information in forming impressions of the focal objects.

In sum, research using implicit and explicit measures provides mixed support for the idea that mere co-occurrence can have unintentional effects when people intentionally use contrastive relational information in forming impressions. When a CS has a contrastive relation to a co-occurring US, CS evaluations on explicit measures are typically opposite to the valence of the co-occurring US (e.g., more favorable evaluation of sunscreen in response to the message *sunscreen prevents skin cancer*), indicating that the contrastive relation influenced intentionally formed impressions. Yet, effects on implicit measures are inconsistent across studies, in that some studies found CS evaluations reflecting the valence of the US regardless of their relation (e.g., less favorable evaluation of sunscreen in response to the message *sunscreen prevents skin cancer*); some studies found CS evaluations that were opposite to the valence of the co-occurring US (e.g., more favorable evaluation of sunscreen in response to the message *sunscreen prevents skin cancer*); and some studies have found no effect at all (e.g., no change in the evaluation of sunscreen in response to the message *sunscreen prevents skin cancer*). Although a small number of studies has identified factors that make mere co-occurrence effects on implicit measures more or less likely to occur, the available evidence in research using implicit and explicit measures to study unintentional influences in intentional impression formation is mixed and somewhat inconsistent. As we explain in the next section, at least some of these inconsistencies may be due to methodological limitations of using a task-dissociation approach to identify effects of mere co-occurrence and relational information.

Evidence in Research Using Multinomial Modeling

A major disadvantage of using a combination of implicit and explicit measures to identify effects of mere co-occurrence and relational information is that the two kinds of measures differ in numerous ways (for a discussion, see Payne et al., 2008). The large number of differences makes it impossible to identify which of these differences is responsible for the differential sensitivity to mere co-occurrence and relational information (see also Bading et al., 2020; Green et al., 2021). A superior approach that resolves this problem is the use of formal modeling procedures to estimate the impact of mere co-occurrence and relational information on responses within a single task. Indeed, research using multinomial modeling (Batchelder & Riefer, 1999; Erdfelder et al., 2009; Hütter & Klauer, 2016) to quantify effects of mere co-occurrence and relational information (e.g., Gawronski & Brannon, 2021; Heycke & Gawronski, 2020; Kukken et al., 2020) has obtained much more consistent evidence compared to studies that have used a task-dissociation approach.

The basic idea underlying the multinomial modeling approach can be illustrated by means of a processing tree that specifies potential patterns of responses to a target object as a function of whether the object has either an assimilative or a contrastive relation to either a positive or a negative stimulus (see Figure 11.1). The four paths on the left side of the figure depict the four potential cases that (1) responses to the object are driven by its relation to a co-occurring stimulus, (2) responses to the object are driven by its mere co-occurrence with the stimulus, (3) responses to the object are driven by a general positivity bias, and (4) response to the object are driven by a general negativity bias. The table on the right side of the figure depicts the response patterns for each of the four cases as a function of relational information and the valence of the co-occurring stimulus.

If responses to a given object are driven by relational information, participants should show a positive response when the object has an assimilative relation with a positive stimulus or a contrastive relation with a negative stimulus, and participants should show a negative response when the object has a contrastive relation with a positive stimulus or an assimilative relation with a negative stimulus (first path in Figure 11.1). If responses to a given object are driven by mere co-occurrence, participants should show a positive response when the object co-occurs with a positive stimulus and a negative response when the objects co-occurs with a negative stimulus (second path in Figure 11.1). If responses to a given object are driven by a general positivity bias, participants should show a positive response regardless of the valence of

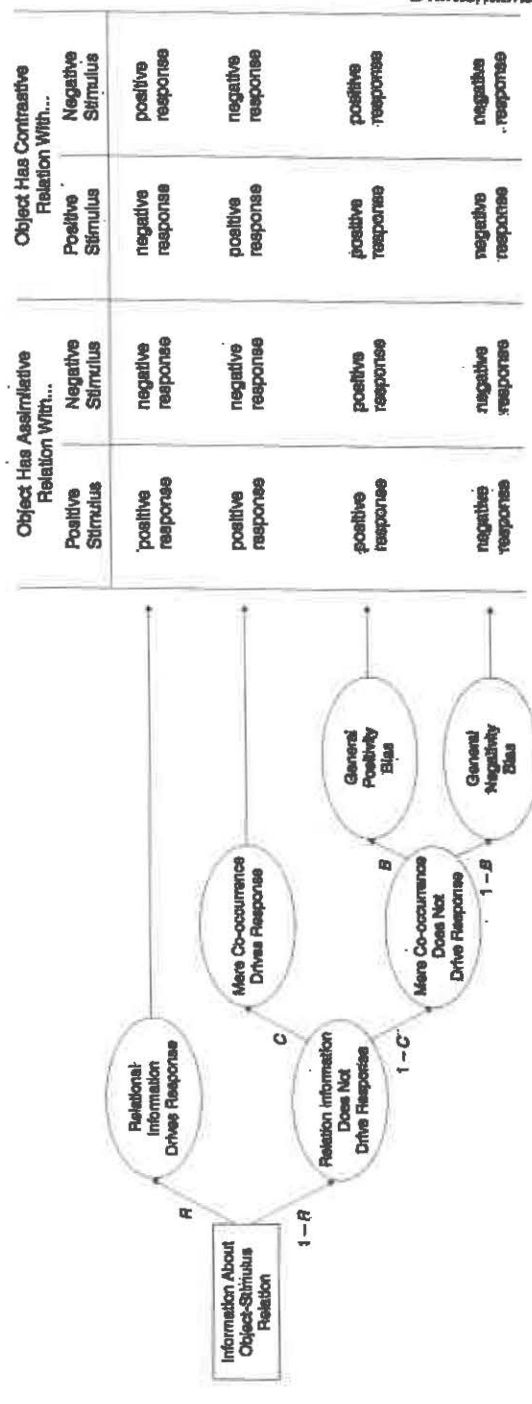

Figure 11.1 Multinomial processing tree depicting effects of relational information, mere co-occurrence, and general response biases on evaluative responses (positive response vs. negative response) as a function of relational information (assimilative relation vs. contrastive relation) and valence of co-occurring stimulus (positive stimulus vs. negative stimulus).

the co-occurring stimulus and the object's relation to that stimulus (third path in Figure 11.1). Conversely, if responses to a given object are driven by a general negativity bias, participants should show a negative response regardless of the valence of the co-occurring stimulus and the object's relation to that stimulus (fourth path in Figure 11.1).

Based on the processing tree depicted in Figure 11.1, multinomial modeling provides numerical estimates for (1) the probability that relational information drives responses (captured by the parameter *R* in Figure 11.1); (2) the probability that mere co-occurrence drives responses if relational information does not drive responses (captured by the parameter C in Figure 11.1); and (3) the probability that a general positivity or negativity bias drives responses if neither relational information nor mere co-occurrence drive responses (captured by the parameter *B* in Figure 11.1).[3] Numerical scores for the three probabilities are estimated by means of four non-redundant mathematical equations derived from the processing tree (see Appendix).[4] These equations include the three model parameters (*R*, *C*, *B*) as unknowns and the empirically observed probabilities of *positive* versus *negative* responses in the four object conditions (i.e., assimilative relation to positive stimulus; assimilative relation to negative stimulus; contrastive relation to positive stimulus; contrastive relation to negative stimulus) as known numerical values. Using maximum likelihood statistics, multinomial modeling generates numerical estimates for the three unknowns that minimize the discrepancy between the empirically observed probabilities of positive versus negative responses in the four object conditions and the probabilities of positive versus negative responses predicted by the model equations using the generated parameter estimates.

The adequacy of the model in describing the data can be evaluated by means of goodness-of-fit statistics, with poor model fit being reflected in a statistically significant discrepancy between the empirically observed probabilities in a given data set and the probabilities predicted by the model. The estimated scores for each parameter can vary between 0 and 1. For the R parameter, scores significantly greater than zero indicate that responses were affected by relational information. For the C parameter, scores significantly greater than zero indicate that responses were affected by mere co-occurrence. Finally, for the B parameter, scores significantly greater than 0.5 indicate a general positivity bias and scores significantly lower than 0.5 indicate a general negativity bias.

Differences from these reference points can be tested by enforcing a specific value for a given parameter and comparing the fit of the restricted model to the fit of the unrestricted model. If setting a given parameter equal to a specific reference point leads to a significant reduction in model fit, it can be inferred that the parameter estimate is significantly different from that reference point. For example, to test whether mere co-occurrence influenced responses, the C parameter is set equal to zero and the resulting model fit is compared to the fit of the model that does not include any restrictions for the C parameter. To the extent that enforcing a parameter estimate of zero leads to a significant reduction in model fit, it can be inferred that mere co-occurrence significantly influenced participants' responses. The same approach can be used to test the influence of relational information captured by the R parameter. For the B parameter, comparisons to reference values are equivalent, except that the reference value reflecting the absence of a general response bias is 0.5. Similar tests can be conducted to investigate whether estimates for a given parameter significantly differ across groups, which can be tested by enforcing equal estimates for that parameter across groups. If setting a given parameter equal across groups leads to a significant reduction in model fit, it can be inferred that the parameter estimates for the two groups are significantly different.

A major advantage of the multinomial modeling approach is that it allows researchers to quantify effects of mere co-occurrence and relational information to overt responses on a single task, and this task can be rather simple (e.g., binary forced-choice judgments) without requiring a high level of procedural complexity (as it is the case for implicit measures). For example, combining Moran and Bar-Anan's (2013) impression-formation paradigm with a simple forced-choice task, Kukken et al. (2020) found that participants' responses to the alien creatures were influenced by both (1) their mere co-occurrence with a pleasant or unpleasant sound and (2) their particular relation to the co-occurring sound (i.e., whether they started or stopped the sound). Similarly, combining Hu et al.'s (2017) impression-formation paradigm with a simple forced-choice task, Heycke and Gawronski (2020) found that participants' responses to the pharmaceutical products were influenced by both (1) their mere co-occurrence with a pleasant or unpleasant health condition and (2) their particular relation to the co-occurring health condition (i.e., whether they caused or prevented the health condition). Interestingly, Heycke and Gawronski obtained reliable effects of mere co-occurrence with a procedural setup that failed to produce mere co-occurrence effects on implicit measures in Hu et al.'s research (Experiment 3). Although studies using a multinomial modeling approach have identified several contextual factors that moderate the relative impact of mere co-occurrence and relational information (see below), the obtained results provide strong support for the idea that mere co-occurrence can have unintentional effects when people intentionally use contrastive relational information in forming impressions.

Theoretical Explanations

A common explanation for joint effects of mere co-occurrence and relational information is that they are the products of two functionally distinct mechanisms operating during the learning of new information. For example, according to the associative-propositional evaluation (APE) model (Gawronski & Bodenhausen, 2006, 2011, 2014, 2018), mere co-occurrence effects are the product of an associative learning mechanism involving the automatic formation of mental associations between co-occurring stimuli. In contrast, effects of relational information are claimed to be the product of a propositional learning mechanism involving the non-automatic generation and truth assessment of mental propositions about the relation between co-occurring stimuli. Based on the hypothesis that effects of mere co-occurrence and relational information are mediated by two distinct learning mechanisms, such accounts have been described as *dual-process learning accounts*.

An alternative explanation is offered by theories that interpret all learning effects as outcomes of a single propositional mechanism involving the non-automatic generation and truth assessment of mental propositions about stimulus relations (e.g., De Houwer, 2009, 2018; De Houwer et al., 2020). According to these theories, distinct effects of mere co-occurrence and relational information result from processes during the retrieval of stored propositional information rather than two functionally distinct learning mechanisms. For example, based on the assumptions of the integrated propositional model (IPM; De Houwer, 2018), mere co-occurrence effects can be expected to occur despite the successful learning of contrastive relational information when the retrieval of a stored proposition about a contrastive relation is incomplete (e.g., retrieval of A *is related to* B rather than A *stops* B; see Van Dessel et al., 2019). Based on the hypothesis that effects of mere co-occurrence and relational information can arise from a single propositional learning mechanism, such accounts have been described as *single-process learning accounts*.[5]

A major difference between the two accounts concerns the presumed (in)dependence of contextual effects on the impact of mere co-occurrence and relational information. Dual-process learning accounts such as the APE model suggest that contextual effects on the impact of mere co-occurrence and relational information are largely independent, in that a given factor may influence one without affecting the other. The critical question is whether a given contextual factor influences either (1) the automatic formation of mental associations between co-occurring stimuli or (2) the non-automatic generation and truth assessment of mental propositions about the relation between co-occurring stimuli (see Gawronski & Bodenhausen, 2006, 2007, 2011, 2018). In contrast, single-process learning accounts such as the IPM suggest that contextual factors should moderate the impact of mere co-occurrence and relational information in a complementary fashion. According to single-process learning theories, effects of mere co-occurrence in cases involving contrastive relations are due to incomplete retrieval of stored propositions about the relation between co-occurring stimuli. Thus, any factor that supports complete retrieval of stored propositions should increase the impact of relational information and reduce the impact of mere co-occurrence. Conversely, any factor that interferes with a complete retrieval of stored propositions should decrease the impact of relational information and increase the impact of mere co-occurrence (see De Houwer, 2018; De Houwer et al., 2020; Van Dessel et al., 2019).

The multinomial modeling approach is ideally suited for empirical tests of these competing predictions, because it permits experimental manipulations of contextual conditions during learning and retrieval while keeping everything else constant (Heycke & Gawronski, 2020). The latter is not feasible with the task-dissociation approach comparing responses on implicit and explicit measures, because it always includes multiple procedural differences between measurement instruments in addition to the focal difference of interest in the experimental manipulation (see Corneille & Mertens, 2020; Sherman et al., 2014). In the following sections, we review empirical evidence that speaks to competing predictions derived from dual-process and single-process accounts regarding the impact of various contextual conditions during learning and retrieval. In line with the proclaimed superiority of the multinomial modeling approach in testing these predictions, we focus specifically on studies that quantified effects of mere co-occurrence and relational information via multinomial modeling. Although some of the reviewed findings pose a challenge to both dual-process and single-process learning accounts, the available evidence provides valuable insights into unintentional influences in intentional impression formation by identifying factors that do or do not moderate such influences.

Time for Encoding

The amount of time devoted to the processing of new information during learning is an important determinant of memory strength (Craik & Lockhart, 1972). The more people elaborate on new information during encoding, the more likely it is that this information is successfully retrieved at a later time. These assumptions are shared by both dual-process and single-process accounts, which both suggest that more time for encoding should support the storage of relational information during learning, and thereby its subsequent retrieval. Hence, both dual-process and single-process accounts suggest that more time for encoding should increase effects of relational information. Yet, the two accounts have different implications for effects of mere co-occurrence. According to dual-process learning accounts, mere co-occurrence effects result from the automatic formation of mental associations between co-occurring stimuli, which should be independent of the available time to elaborate on new information. Thus, although more time for encoding should increase the impact of relational information, the impact of mere co-occurrence should be unaffected by time for encoding. In contrast, single-process learning accounts assume that mere co-occurrence effects result from incomplete retrieval of stored propositions about the relation between co-occurring stimuli. Thus, to the extent that more time for encoding supports the complete retrieval of stored information, it should increase the impact of relational information and reduce the impact of mere co-occurrence. Evidence addressing this question was presented by Heycke and Gawronski (2020, Experiments 2a and 2b) who found that more time for encoding significantly increased the impact of relational information (consistent with both accounts) without affecting the impact of mere co-occurrence (consistent with dual-process learning accounts).

Repetition

Although dual-process learning accounts suggest that mere co-occurrence effects should be unaffected by how much people elaborate on new information, they predict that mere co-occurrence effects should increase as a function of repetition. This prediction is based on the assumption that mental associations between two stimuli should become stronger with increasing frequency of their co-occurrence (Smith & DeCoster, 2000). At the same time, repetition should support the storage of information about stimulus relations, and thereby the subsequent retrieval of this information. From this perspective, repetition should increase effects of both mere co-occurrence and relational information. In contrast, from a single-process learning view, repetition should support the storage of information about stimulus relations, and thereby a complete retrieval of this information. From this perspective, repetition should increase effects of relational information and decrease effects of mere co-occurrence. Interestingly, the available evidence regarding the impact of repetition on mere co-occurrence effects conflicts with both accounts. Specifically, Heycke and Gawronski (2020, Experiment 3) found that repetition significantly increased the impact of relational information (consistent with both accounts), but repetition had no significant effect on the impact of mere co-occurrence (inconsistent with both accounts).

Time during Judgment

Although dual-process and single-process learning accounts lead to different predictions regarding the impact of time for encoding, the two accounts have the same implications for the impact of time during judgment. According to dual-process accounts such as the APE model, effects of activated associations on judgments and behavior should be reduced when deliberate propositional reasoning leads to a rejection of the spontaneous evaluative response elicited by automatically activated associations (Gawronski & Bodenhausen, 2006, 2007, 2011, 2018). From this perspective, more time during judgment should have compensatory effects, in that it should increase effects of relational information and decrease effects of mere co-occurrence. Similarly, single-process accounts such as the IPM suggest that more time during judgment should support a complete retrieval of stored information about stimulus relations, which should increase effects of relational information and decrease effects of mere co-occurrence. Interestingly, the available evidence conflicts with the shared prediction regarding the impact of time during judgment on mere co-occurrence effects. Specifically,

Heycke and Gawronski (2020, Experiment 4) found that more time during judgment increased the impact of relational information (consistent with both accounts), but it also increased—rather than decreased—the impact of mere co-occurrence (inconsistent with both accounts).

Temporal Delay

Another factor for which the two accounts lead to different predictions is the temporal delay between encoding and judgment. Some dual-process learning accounts suggest that mental representations of relational information involve multiple layers within associative networks (Smith & DeCoster, 2000). According to such multi-layer network theories, activated concepts at higher levels specify the relation between activated concepts at lower levels (Gawronski & Bodenhausen, 2018; Gawronski et al., 2017). Thus, to the extent that hierarchical representations involving multiple layers of associative links are more likely affected by memory decay compared to direct associative links between two concepts, effects of mere co-occurrence should be more stable over time compared to effects of relational information. From this perspective, longer temporal delays between encoding and judgment should reduce the impact of relational information, with the impact of mere co-occurrence being less affected by temporal delays. In contrast, single-process learning accounts suggest that memory decay associated with temporal delays should increase the likelihood of incomplete retrieval of stored information about stimulus relations. From this perspective, a longer temporal delay between encoding and judgment should decrease effects of relational information and increase effects of mere co-occurrence. Evidence addressing this question was presented by Heycke and Gawronski (2020, Experiment 5) who found that a two-day delay between encoding and judgment decreased the impact of relational information (consistent with both accounts) without affecting the impact of mere co-occurrence (consistent with dual-process learning accounts).

Intentional Control

Another difference between the two accounts concerns the presumed impact of intentional control. According to dual-process learning accounts, enhanced attention to relational information during encoding should support the storage of this information, thereby increasing its effect on judgments. However, enhanced attention to relational information during encoding should have little impact on the effect of mere co-occurrence, which is assumed to result from the automatic formation of mental associations between co-occurring stimuli (see Gawronski & Bodenhausen, 2014). From this perspective, enhanced motivation to intentionally control the impact of mere co-occurrence by focusing on stimulus relations should increase the impact of relational information without affecting the impact of mere co-occurrence. In contrast, single-process learning accounts suggest that enhanced attention of relational information during encoding should support the storage of information about stimulus relations, and thereby the complete retrieval of this information. From this perspective, enhanced motivation to intentionally control the impact of mere co-occurrence by focusing on stimulus relations should increase the impact of relational information and decrease the impact of mere co-occurrence. Evidence addressing this question was presented by Gawronski and Brannon (2021) who found that enhanced motivation to intentionally control the impact of mere co-occurrence by focusing on stimulus relations increased the impact of relational information (consistent with both accounts) without affecting the impact of mere co-occurrence (consistent with dual-process learning accounts). Similar findings were obtained by Kukken et al. (2020, Experiment 4).

Summary

Research testing competing predictions of dual-process and single-process learning accounts has provided valuable insights into unintentional influences in intentional impression formation by identifying factors that do moderate such influences and factors that do not. In line with the shared predictions of dual-process and single-process accounts, effects of relational information have been found to increase with more time for encoding, more frequent repetition, more time during judgment, shorter delays between encoding and judgment, and stronger motivation to process relational information. However, the two accounts fared less well in predicting the influence of these contextual factors on the effects of mere co-occurrence, which are the hallmark of unintentional influences in intentional impression formation. On the one hand, mere co-occurrence effects were unaffected by time for encoding, temporal delay, and intentional control. These results are consistent with the predictions of dual-process learning accounts and inconsistent with the predictions of single-process learning accounts. On the other hand, mere co-occurrence effects were unaffected by repetition and they increased with more time during judgment. These results are inconsistent with the predictions of both dual-process and single-process learning accounts. Although the latter findings raise important questions about the mental processes underlying mere co-occurrence effects, it is worth noting that they still provide valuable insights into the boundary conditions of unintentional influences in intentional impression formation, as reflected in dissociative effects of mere co-occurrence and relational information. Specifically, the available evidence suggests that unintentional influences in intentional impression formation are unaffected by time for encoding, repetition, temporal delay, and intentional control, but ironically increase with more time during judgment. An important task for future research is to investigate why these factors show the obtained effects, which could provide further insights into the processes underlying unintentional influences in intentional impression formation.

Implications for Social Impression Formation

Although extant theories are still facing empirical challenges in accounting for the moderators of unintentional influences in intentional impression formation, the phenomenon itself is supported by a solid body of evidence. While some of this research involves impressions of non-social objects (e.g., Gawronski & Brannon, 2021; Heycke & Gawronski, 2020; Hu et al., 2017), there is considerable evidence suggesting that unintentional influences can also occur for intentional impressions of social targets (e.g., Kukken et al., 2020; Moran & Bar-Anan, 2013; Moran et al., 2015). An interesting extension of the latter work is research on contrastive relations in social networks. Research on cognitive balance (Heider, 1958) suggests that interpersonal sentiments can influence social impressions in a manner similar to the relational information in the reviewed research. Whereas positive relations (e.g., liking someone, being liked by someone) have been found to influence social impressions in an assimilative manner, negative relations (e.g., disliking someone, being disliked by someone) tend to influence social impressions in a contrastive manner. For example, people tend to form positive impressions of individuals who are liked by a positively evaluated person and negative impressions of individuals who are liked by a negatively evaluated person. Conversely, people tend to form negative impressions of individuals who are disliked by a positively evaluated person and positive impressions of individuals who are disliked by a negatively evaluated person (e.g., Aronson & Cope, 1968; Gawronski et al., 2005; Langer et al., 2009). These findings raise the question of whether mere co-occurrence can influence social impressions when two individuals are known to have contrastive relations (e.g., they dislike each other).

Yet, counter to this idea, research using implicit and explicit measures suggests that relational information prevails over mere co-occurrence in impression formation based on social networks (e.g., Gawronski & Walther, 2008; Gawronski et al., 2005). Moreover, under conditions where mere co-occurrence has been found to influence responses on implicit measures, it also influenced responses on explicit measures with relational information being ineffective in influencing social impressions (e.g., Gawronski & Walther, 2008; Gawronski et al., 2005). These results suggest that unintentional influences of mere co-occurrence are unlikely to occur for intentional impressions of people based on their interpersonal relations in social networks.

That being said, all of this research has relied on a task-dissociation approach comparing responses on implicit and explicit measures. Considering that multinomial modeling has been found to be more sensitive in detecting mere co-occurrence effects that remain undetected by the task-dissociation approach, an interesting question for future research is whether multinomial modeling is also superior in detecting mere co-occurrence effects in impression formation based on social networks. We consider this question as an interesting direction for future research.[6]

An important theoretical insight of the reviewed research is the significance of distinguishing between (1) processes involved in the formation of mental representations and (2) processes involved in the behavioral expression of stored representations. Early domain-specific dual-process theories have been very precise about whether their assumptions refer to the formation of a mental representation or the effects of a stored representation on behavior. However, the distinction has become increasingly blurry in domain-independent dual-system theories (e.g., Epstein, 1994; Kahneman, 2003; Smith & DeCoster, 2000; Strack & Deutsch, 2004), which explain all social phenomena as the interactive product of two functionally distinct processing systems (for a discussion, see Gawronski, Luke, & Creighton, in press). In line with the rediscovered significance of distinguishing between the formation and behavioral expression of mental representations (e.g., Corneille & Stahl, 2019; De Houwer et al., 2020; Gawronski et al., 2017; Kurdi & Dunham, 2020; Mandelbaum, 2016; see also Ferguson et al., 2014), the reviewed debate on the processes underlying unintentional influences in intentional impression formation suggests that other research on social impressions might similarly benefit from drawing sharper distinctions between the two stages. An illustrative example is the modal approach in research on spontaneous social inferences, which is based on the assumption that spontaneous impressions can be identified by means of non-reactive measures that do not require intentional judgments of the focal targets. Examples of such non-reactive measures are cued recall tasks, recognition tasks, lexical-decision tasks, word-stem-completion tasks, and relearning tasks (see Uleman et al., 1996). However, in a strict sense, these non-reactive tasks ensure only the role of unintentional processes in the behavioral expression of stored impressions, but they do not ensure the role of unintentional processes in their formation. Thus, greater attention to the distinction between the formation and behavioral expression of mental representations may also provide more nuanced insights into the processes underlying spontaneous social impressions.

Conclusions

The current chapter reviewed evidence for unintentional influences in intentional impression formation, focusing particularly on the phenomenon that the mere co-occurrence of stimuli can influence evaluative responses in a manner that is diametrically opposite to intentionally formed impressions based on the relation between the co-occurring stimuli. This phenomenon is similar to spontaneous social inferences, in that it involves unintentional effects in impression formation. However, it is different from spontaneous social inferences, in that it arises in contexts where people do have the intention to form an impression. Moreover, while prior research on spontaneous inference has predominantly focused on impressions with specific semantic content, evidence for unintentional influences in intentional impression formation primarily comes from studies on broad evaluative impressions. Although extant theories are facing some non-trivial challenges in accounting for the moderators of such unintentional influences, the phenomenon itself is supported by a considerable body of evidence in research using task-dissociation and formal modeling approaches. An important task for future research is to develop mental-process theories that explain not only the phenomenon itself, but also its (in)sensitivity to various contextual factors.

Notes

1 Author's Note: Preparation of this chapter was supported by National Science Foundation Grant #1649900. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

2 A notable exception to these modal trends is recent research on spontaneous evaluative inferences (e.g., Olcaysoy Okten et al., 2019; Schneid et al., 2015).

3 Following Heycke and Gawronski (2020), we use R for the parameter capturing effects of relational information, C for the parameter capturing effects of mere co-occurrence, and B for the parameter capturing general response biases. In a multinomial model that is structurally equivalent to the model in Figure 11.1, Kukken et al. (2020) used *m* instead of *R* (referring to meaning), *p* instead of C (referring to pairing), and *g* instead of B (referring to guessing).

4 Because multinomial modeling is based on binary responses with p(positive response) = 1 – p(negative response), there are only four non-redundant equations in the set of eight equations listed in the Appendix.

5 An alternative way to explain effects of mere co-occurrence and relational information from a single-process propositional view is to hypothesize that people generate and store two propositions for the same event, one capturing relational information (e.g., X prevents something negative) and one capturing co-occurrence information (e.g., X co-occurs with something negative). Expanding on this hypothesis, unintentional effects of mere co-occurrence despite intentional use of relational information can be explained with the additional assumption that mental propositions capturing co-occurrence information are generated and retrieved automatically. However, it is worth noting that such an explanation would make single-process propositional accounts empirically indistinguishable from accounts that propose two functionally distinct learning mechanisms, rendering the debate a matter of terminological preference rather than empirical evidence. While dual-process learning accounts explain mere co-occurrence effects in terms of automatic formation of associations between co-occurring stimuli, single-process propositional accounts endorsing the above assumptions would explain mere co-occurrence effects in terms of automatic processing of co-occurrence propositions.

6 An important caveat is that the standard model depicted in Figure 11.1 (see Heycke & Gawronski, 2020; Kukken et al., 2020) would have to be extended with an additional parameter capturing evaluative effects of interpersonal sentiments independent of the valence of the "co-occurring" person. Such an extension may be required, because being liked by someone has been found to lead to more favorable impressions than being disliked by someone, regardless of whether the (dis)liking person is evaluated positively or negatively (e.g., Gawronski et al., 2005). Similarly, liking someone has been found to lead to more favorable impressions than disliking someone regardless of whether the (dis)liked person is evaluated positively or negatively (e.g., Gawronski & Walther, 2008). These effects will have to be accounted for when applying a

multinomial modeling approach to studying effects of mere co-occurrence and relational information in impression formation based on social networks.

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Appendix

Model equations for the estimation of effects of relational information (R), mere co-occurrence (C), and general response bias (B) on responses to objects that have an assimilative or a contrastive relation to a positive or a negative stimulus.

p(positive response | assimilative, positive) = $R + [(1 - R) \times C] + [(1 - R) \times (1 - C) \times B]$

p(positive response | assimilative, negative) = $(1 - R) \times (1 - C) \times B$

p(positive response | contrastive, positive) = $[(1 - R) \times C] + [(1 - R) \times (1 - C) \times B]$

p(positive response | contrastive, negative) = $R + [(1 - R) \times (1 - C) \times B]$

p(negative response | assimilative, positive) = $(1 - R) \times (1 - C) \times (1 - B)$

p(negative response | assimilative, negative) = $R + [(1 - R) \times C] + [(1 - R) \times (1 - C) \times (1 - B)]$

p(negative response | contrastive, positive) = $R + [(1 - R) \times (1 - C) \times (1 - B)]$

p(negative response | contrastive, negative) = $[(1 - R) \times C] + [(1 - R) \times (1 - C) \times (1 - B)]$